



Posters

From the Grid Science Winter School

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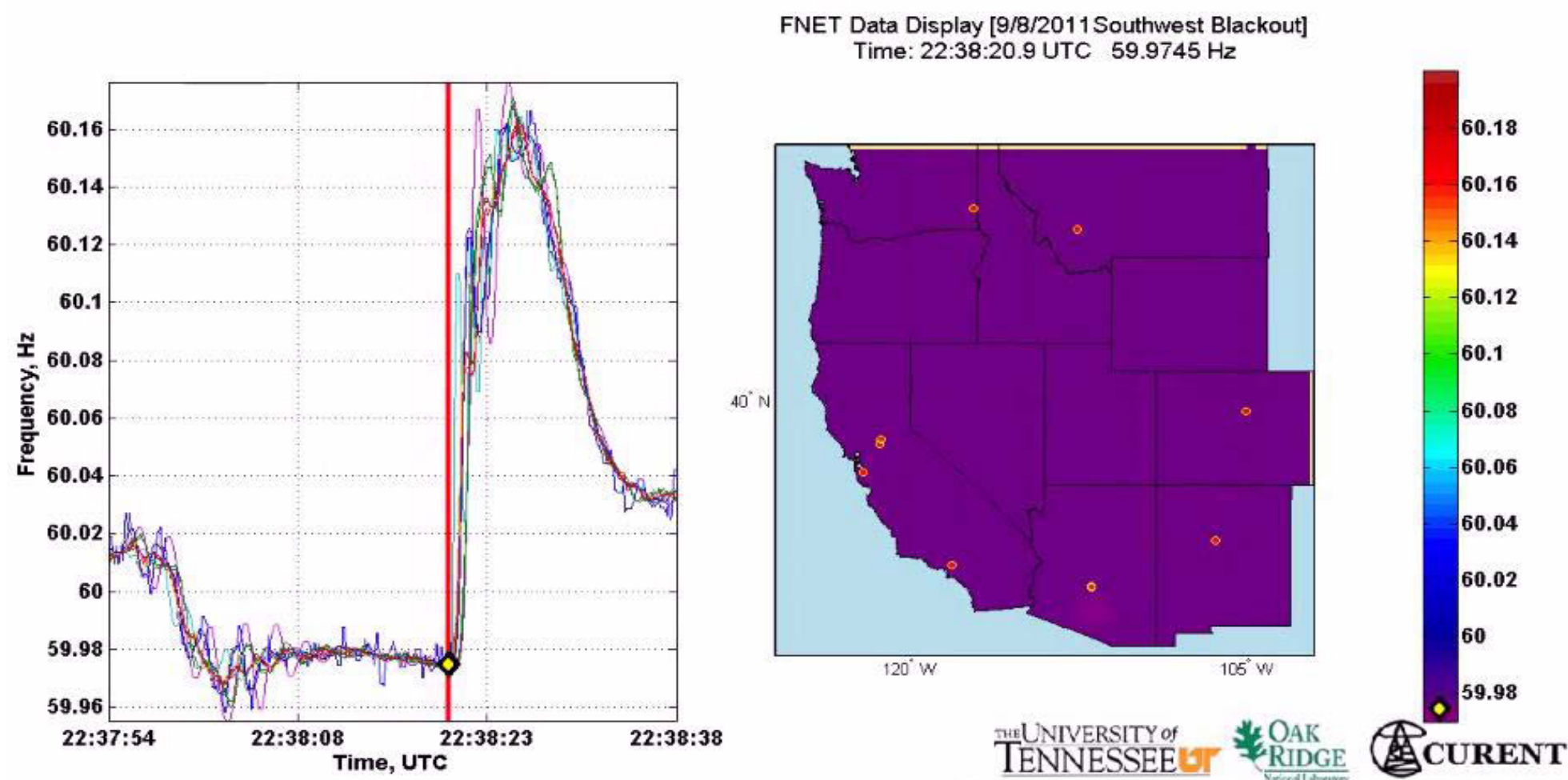
Decentralized Primary Frequency Control in Power Networks

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Motivation

- Normal operation of power networks: all buses synchronized to nominal frequency (60 Hz)
- Supply-demand imbalance → frequency deviation**
degrade load performance; overload transmission lines; trigger protection devices; damage equipment



WECC frequency profile, 9/8/2011 Southwest Blackout

Primary frequency control: balance power and stabilize frequency

- Traditionally done on generator side
- Increased power intermittency (33% renewable in CA by 2020) requires faster and more spinning reserves, which have higher cost and emission

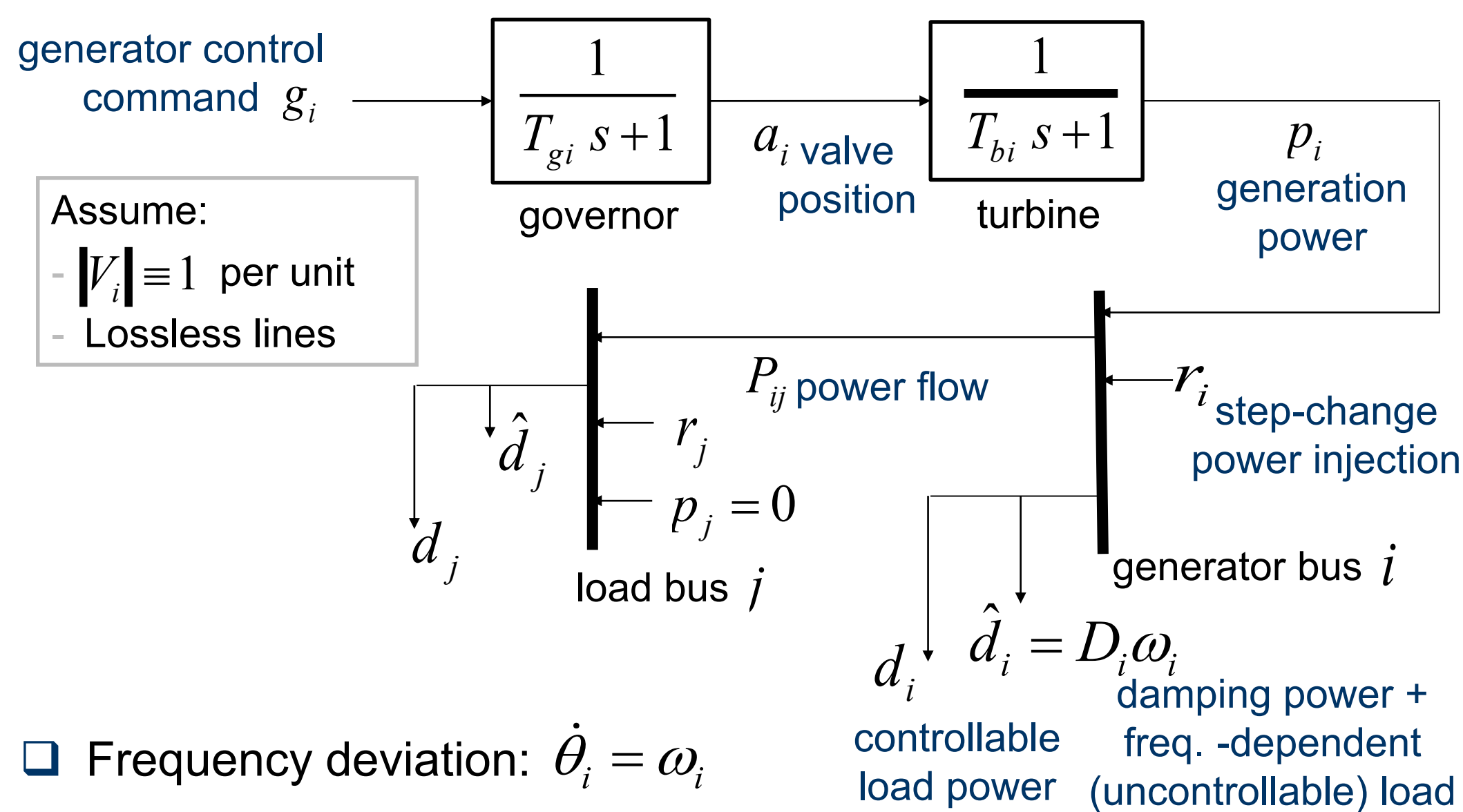
Load-side participation in primary frequency control

- A faster and cleaner supplement to generator-side
- Decentralized control for scalable and flexible plug-n-play
- Challenge: Joint design and stability analysis with generator-side (purpose of this work)

Main Results

- Design decentralized primary frequency control which operates jointly on generators and loads
- Stabilize bus frequencies and achieve economic efficiency at closed-loop equilibrium
- Prove asymptotic stability with a relatively realistic generator model and nonlinear AC power flows
- Show performance improvement with simulation

Power Network Model



- Frequency deviation: $\dot{\theta}_i = \omega_i$
- Swing equation (generator-bus):
$$M_i \dot{\omega}_i = r_i + p_i - d_i - \hat{d}_i - \sum_{j \in N(i)} P_{ij}$$
- Power balance (load-bus):
$$0 = r_i + p_i - d_i - \hat{d}_i - \sum_{j \in N(i)} P_{ij}$$
- AC power flow: $P_{ij} = B_{ij} \sin(\theta_i - \theta_j)$

Technical Approach

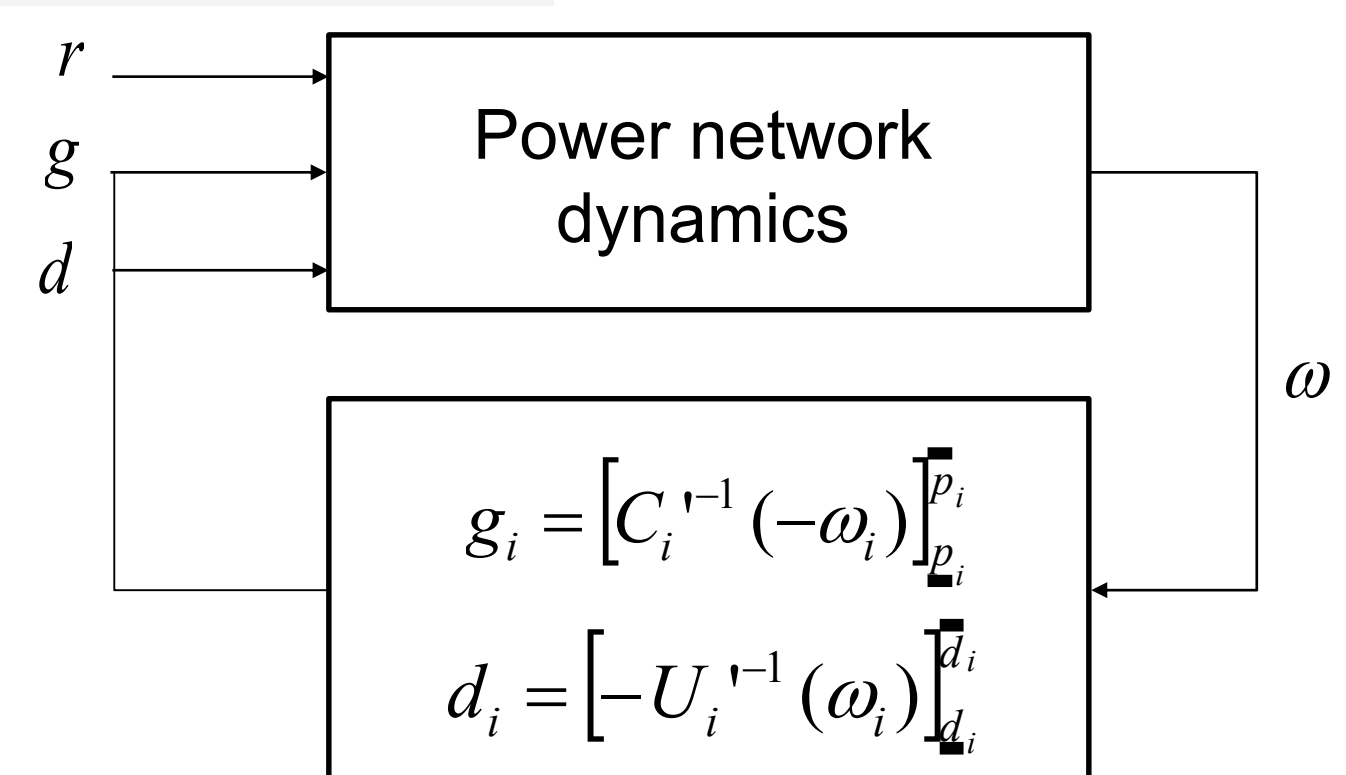
Problem Formulation

Design **decentralized** controllers for (g, d) , such that the closed-loop system has an **asymptotically stable** equilibrium, where $(p^*, d^*, \hat{d}^*, P^*)$ solves the **economic efficiency** problem:

$$\begin{aligned} & \max_{p, d, \hat{d}, P} \quad \sum_i U_i(d_i) - C_i(p_i) - \frac{\hat{d}_i^2}{2D_i} \\ & \text{s.t.} \quad r_i + p_i - d_i - \hat{d}_i - \sum_{j \in N(i)} P_{ij} = 0 \quad \forall i \\ & \quad \quad p_i \leq p_i \leq \bar{p}_i, \quad \underline{d}_i \leq d_i \leq \bar{d}_i \quad \forall i \end{aligned}$$

Labels: user utility (concave), generation cost (convex), penalty for freq. deviation

Controller Design



Equilibrium Analysis

- All closed-loop equilibria are economically efficient
- Dual optimal $\omega_i^* = \omega_j^*$: Bus frequencies stabilized to the same
 - Proof approach: Equilibrium condition \Rightarrow KKT condition
 - Need secondary frequency control to restore bus frequencies to the nominal value

Stability analysis

Lyapunov function candidate: $V = E + \sum_{i \in \text{gen}} V_i$

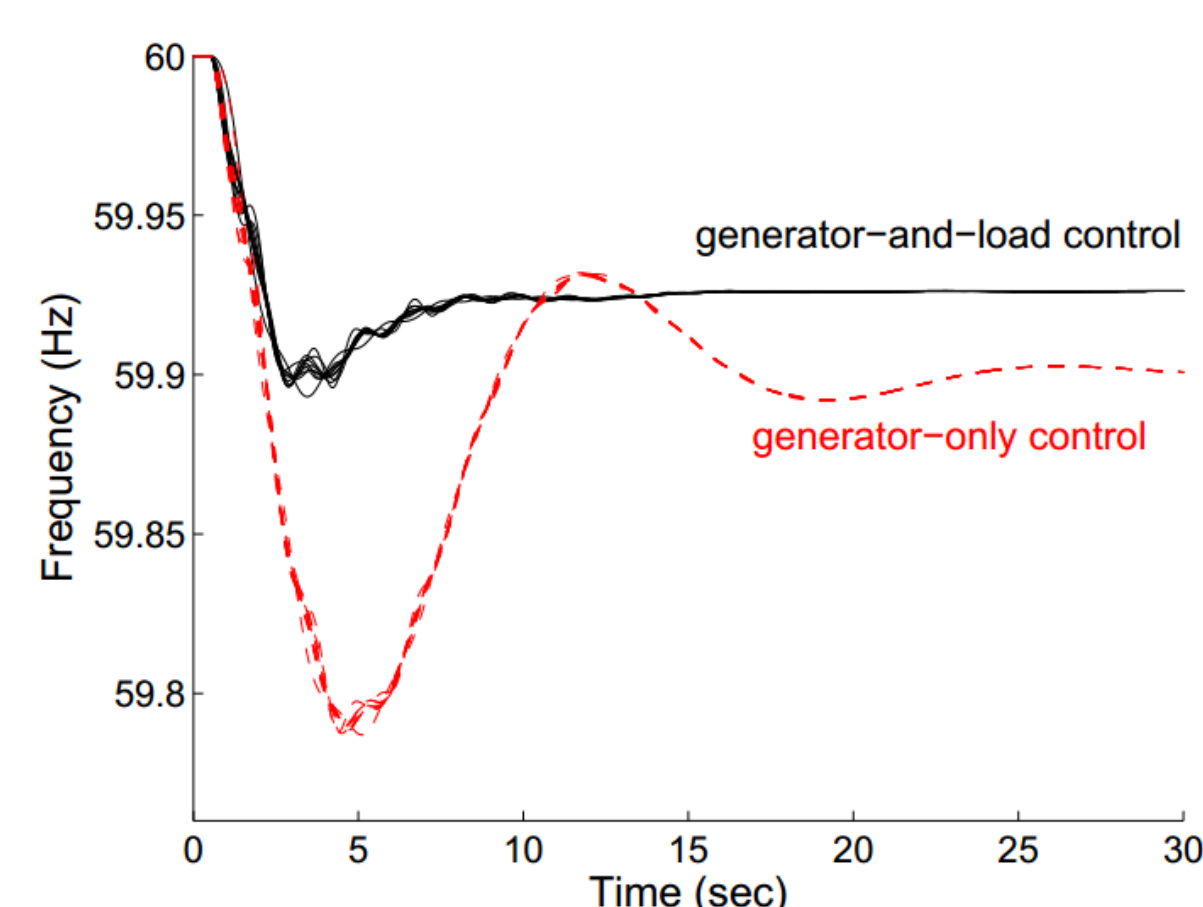
where $E = \frac{1}{2} \sum_{i \in \text{gen}} M_i \Delta \omega_i^2 + \sum_{(i,j) \in \text{line}} \int_{\theta_{ij}^*}^{\theta_{ij}} B_{ij} (\sin u - \sin \theta_{ij}^*) du$
kinetic energy, potential energy

and $V_i = [\Delta a_i, \Delta p_i] P_i [\Delta a_i, \Delta p_i]^T$ with $P_i \succ 0$

Construct P_i such that V is a Lyapunov function, proving asymptotic stability of any equilibrium satisfying mild conditions

Simulation Result

IEEE 39-bus test case, in Power System Toolbox (Chow et al.)



Show generator frequencies when:

- Red:** only generators are controlled
- Black:** 50% control capacity on generators and 50% on loads

Both cases: same total control capacity

Load-side participation improves both steady-state and transient

Introduction

- This work develops a synergistic combination of Markovian and interval optimization for unit commitment problems with wind generation and transmission
- Motivation: Important to accommodate high penetration of wind
 - DOE's goal: **20%** wind by 2030
 - Obama's goal: **80%** clean energy by 2035
 - In Spain, an unprecedented decrease in wind generation in Feb. 2012 is equivalent to the sudden down of 6 nuclear plants (4 is not unusual)
 - Texas Emergency Electric Curtailment Plan is called on in Feb. 2008
- Difficulties:
 - Intermittent/uncertain nature of wind generation
 - Cannot be dispatched as conventional units
 - Large uncertainty: Mean Absolute Error (normalized over capacity) of day-ahead wind power forecast: 15%~20%
 - Complicated structures of transmission networks
 - Computational complexity: NP hard problems

Literature Review

- Stochastic programming
 - Modeling wind generation – Representative scenarios
 - To minimize the expected cost over scenarios
 - Difficult to choose an appropriate number of scenarios to balance computational complexity and solution feasibility
- Robust optimization
 - Uncertainties modeled by an uncertainty set w/o probabilities
 - To optimize against the worst-case realization
 - Min Max conservative and computationally challenging
- Pure interval optimization^[1]
 - Modeling wind generation – Closed intervals w/o probabilities
 - Capturing the bounds of uncertain inputs in different types of constraints, and making decisions feasible for these bounds
 - System demand constraints: As long as min. and max. wind realizations are feasible, other realizations within them will be feasible
 - E.g., wind farm 1 outputs [10 MW, 40 MW], and wind farm 2 [20 MW, 50 MW]. Total wind generation = [30 MW, 90 MW].
 - System demand = 200 MW. Net system demand = [110 MW, 170 MW]
 - If a set of committed units with p_i^{\min} and p_i^{\max} can meet the 110 MW and 170 MW, can it satisfy possible demand at 140 MW?
 - Transmission capacity constraints: $|\text{Power flow}| \leq f_l^{\max}$
 - A line flow is a linear combination of nodal injections weighted by **generation shift factors** (GSFs can be + or -)

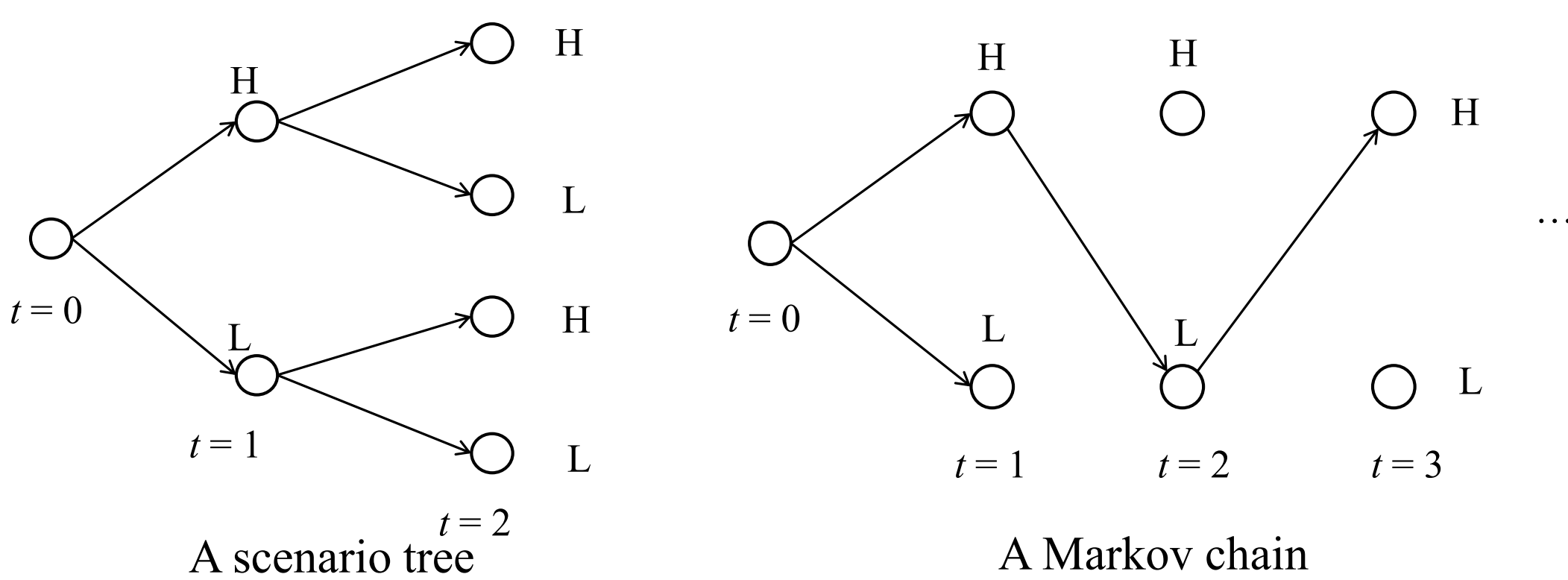
$$f_l(t) = \sum_i a_l^i \left(p_i^I(t) + p_i^W(t) - p_i^L(t) \right), \forall l, \forall t \quad (1)$$
 - “Passively” capture **bounds of uncertain inputs**

$$\sum_i a_l^i p_i(t) \leq f_l^{\max} - \max_i \left[\sum_i a_l^i \left(p_i^W(t) - p_i^L(t) \right) \right] \quad (2)$$

Pre-computed based on interval arithmetic
 - Objective function: To minimize the cost of the expected realization
 - Linear and efficient via interval arithmetic; conservative

Previous Work - Markovian Optimization w/o Transmission^[2]

- Model aggregated wind generation – A Markov chain
 - Given the present, the future is independent of the past



N^T possible scenarios at one node

$T \cdot N$ possible states at one node

- Advantage:** State at a time instant summarizes the information of all previous instants in a probabilistic sense for reduced complexity

- Stochastic UC depends on **states instead of scenarios**

Markovian and Interval Unit Commitment

- Wind model considering transmission constraints**
 - With congestion**, wind generation cannot be aggregated together
 - Wind states for farms at different nodes may not be the same
 - Nearby wind farms: Generation aggregated
 - Wind farms far apart: States assumed independent
 - A Markov chain per node**
 - With I wind nodes (Markov chains): N^I possible global states at time t
 - Curse of dimensionality!**

Key idea: Markov + interval-based optimization

- Markovian analysis to depend on local states; interval analysis to manage extreme combinations of non-local states
 - Local state: Wind generation state at the node under consideration (will be extended into zonal state in future work)
- Physical infrastructure supporting this idea: **Wind-diesel system**
- How to combine two distinct approaches? Divide the generation (dispatch decision) of a conventional unit into two components**
 - Markovian component** depends on the local state n_i

$$x_i(t) p_i^{\min} \leq \boxed{p_{i,n_i}^M(t)} + \boxed{p_{i,n_i}^I(t)} \leq x_i(t) p_i^{\max}, \forall i, \forall t, \forall n_i, \forall \bar{n}_i \quad (3)$$

- Interval component** manages extreme combinations of non-local states
- Constraints innovatively formulated to guarantee solution feasibility for all realizations without much complexity
- The effective use of local wind states alleviates the over-conservativeness of interval optimization

- System demand constraints
 - Based on interval optimization^[1]: **As long as min. and max. global states are feasible, all other realizations within them will be feasible**

$$\underbrace{\sum_i \left(p_{i,\min n_i}^M(t) + p_{i,m_i}^I(t) \right)}_{\text{The minimum local state at node } i} = \sum_j \left(p_i^L(t) - p_{i,\min n_i}^W(t) \right), \forall t \quad (4)$$

The minimum combination of non-local states (where other nodes are at their minimum possible states)

$$\sum_i \left(p_{i,\max n_i}^M(t) + p_{i,M_i}^I(t) \right) = \sum_j \left(p_i^L(t) - p_{i,\max n_i}^W(t) \right), \forall t \quad (5)$$

- Transmission capacity constraints: $|\text{Power flow}| \leq f_l^{\max}$
 - Flexibility of local conventional generation used to shrink ranges of RHS**

$$\sum_i a_l^i p_i^I(t) \leq f_l^{\max} - \max_i \left[\sum_i a_l^i \left(p_{i,n_i}^W(t) + p_{i,n_i}^M(t) - p_i^L(t) \right) \right], \forall l, \forall t \quad (6)$$

Markovian nodal injection $\equiv p_{i,n_i}^M(t)$ (containing decision variables)

- Ramp rate constraints
 - Required for possible local states, local state transitions, $p_{i,m_i}^I(t)$, and $p_{i,M_i}^I(t)$
- The objective function: To approximate the expected cost w/o much complexity
 - A weighted sum of extreme realizations and the expected realization

$$\min \sum_{t=1}^T \sum_{i=1}^I \left[\sum_{n_i=1}^{N_i} \left[w_{n_i,m_i}(t) C_i \left(p_{i,n_i}^M(t) + p_{i,m_i}^I(t) \right) + w_{n_i,M_i}(t) C_i \left(p_{i,n_i}^M(t) + p_{i,M_i}^I(t) \right) \right] \right] \quad (7)$$

Weights adding up to 1
- A **non-linear** MIP formulation
 - Non-linearity lies in max/min (negative flow direction) operations in (6)

Solution Methodology – Branch-and-cut

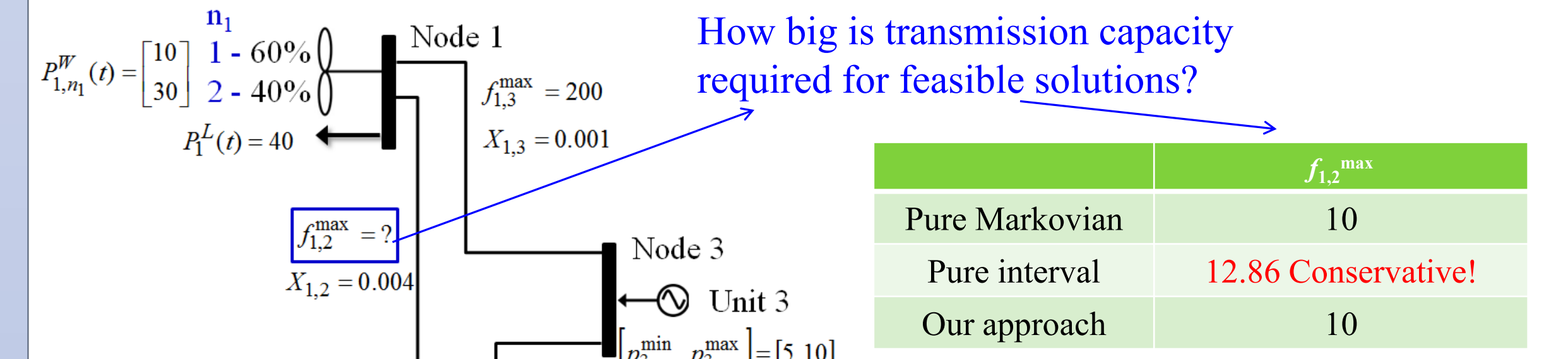
- Max/Min operations transformed into a linear form**
 - Idea:** Analyze the monotonicity of Markovian nodal injections w.r.t. local states, then **select indices of local states w/o optimization**
 - The Monotonicity Conjecture:** The local state with lower wind generation provides less or equal Markovian nodal injection at the optimum, i.e.,

$$P_{i,n_i-1}^M(t) \leq P_{i,n_i}^M(t), \forall i, \forall t, \forall n_i, \forall (n_i-1) \in \{n_i-1 \mid \varphi_{n_i-1}(t) > 0\}. \quad (8)$$
 - Generalized monotonicity analysis** used to support this conjecture

$$\max_{n_i} P_{i,n_i}^M(t) = P_{i,\max n_i}^M(t), \quad \min_{n_i} P_{i,n_i}^M(t) = P_{i,\min n_i}^M(t), \forall i, \forall t. \quad (9)$$
- Overall problem converted linearly after
 - Including (8) as constraints
 - Substituting the min/max operations with corresponding states
- State transition matrices given and state probabilities pre-computed**

Numerical Testing Results

- CPLEX 12.5.1.0 on a PC laptop with an Intel Core(TM) i7-2820QM 2.30GHz CPU and 8GB memory
- Illustrative examples
 - Conservativeness** – Consider 3 nodes, 2 wind farms, 2 units, and 1 hour



	No. of dispatch decisions per unit	No. of flow levels per line
Pure Markovian	10⁶	10⁶
Pure interval	2+1	2+1
Our approach	10 + 2 + 1	2 + 2 + 1

- Complexity** – Consider 6 wind farms at different buses, 10 states for each

- Solution feasibility and modeling accuracy**
 - IEEE 30-bus system with 2 wind farms at 40% wind penetration
 - Free wind curtailment and load shedding at \$5,000/MWh penalty
 - Stopping MIP gap 0.1% and then 10,000 Monte Carlo runs
 - Our approach provides 5.23% lower simulation cost** than pure interval
 - Our approach is the most accurate, as it has the smallest APE[#]**

Approach	Deter.	Interval	Ours
Optimization	CPU time	2s	53s
	Cost (k\$)	248.66	280.67
	Penalty (k\$)	0	0.47
UC cost (k\$)		89.46	67.72
Simulation	E(Cost) (k\$)	314.89	263.26
	APE [#]	21.03%	6.61%
	STD(cost) (k\$)	74.46	33.77
	Penalty (k\$)	40.82	0

[#] Absolute percentage error (APE) = |optimization cost – simulation cost| / simulation cost × 100%

- Computational efficiency**

- IEEE 118-bus system with 3 wind farms

		Ours
Optimization	CPU time	41s
	MIP GAP	0.01%
	Cost (k\$)	911.48
UC Cost (k\$)		12.83
Simulation	E(cost) (k\$)	920.97
	APE	1.03%
	STD(cost) (k\$)	24.64

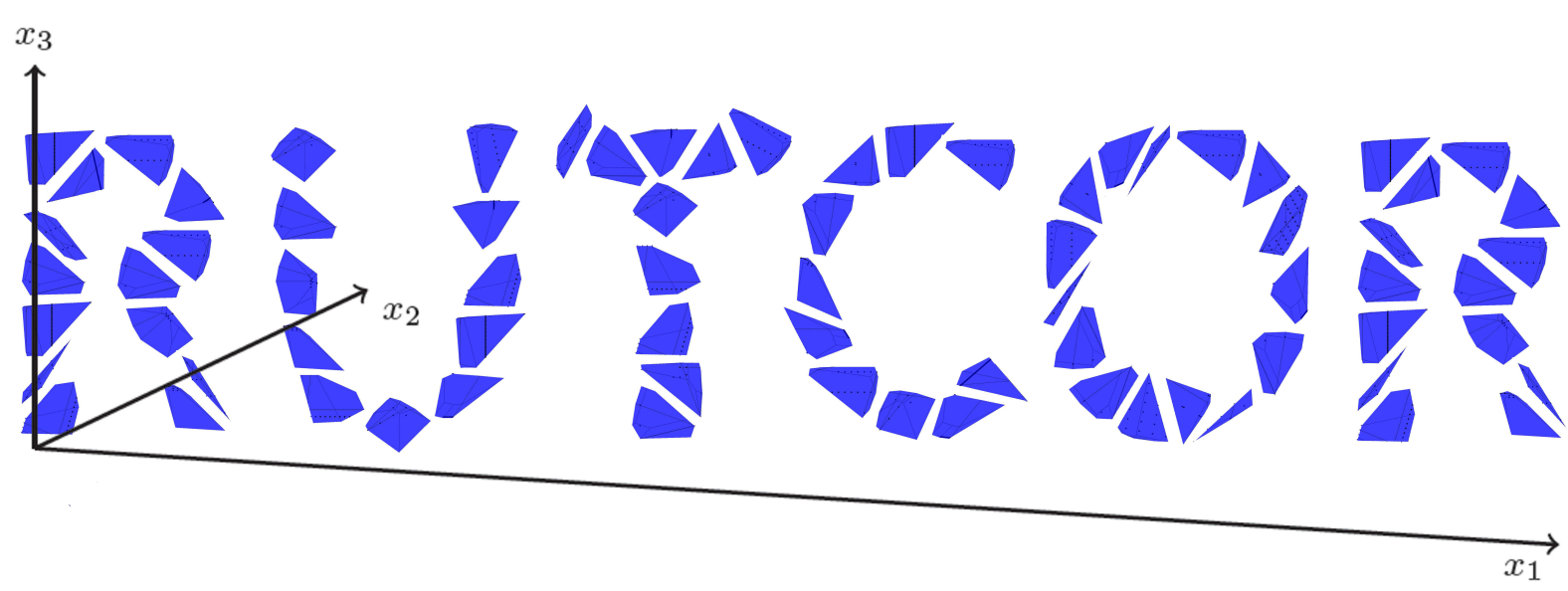
Conclusion

- An important but difficult issue
- Hybrid Markovian and interval optimization to overcome the complexity caused by transmission constraints
 - Markovian analysis to depend on local state/reduce conservativeness
 - Interval analysis to ensure feasibility against realizations
- Problem transformed into a linear form based on monotonicity, and then solved efficiently by using branch-and-cut
- Opens a new and effective way to address stochastic problems w/o scenario analysis and avoid over-conservativeness

References

- Y. Wang, Q. Xia, and C. Kang, “Unit commitment with volatile node injections by using interval optimization,” *IEEE Transactions on Power Systems*, vol. 26, no. 3, pp. 1705-1713, 2011.
- P. B. Luh, Y. Yu, B. Zhang, E. Litvinov, T. Zheng, F. Zhao, J. Zhao, and C. Wang, “Grid integration of intermittent wind generation: A Markovian approach,” *IEEE Trans. Smart Grid*, vol.5, no.2, pp.732-741, March 2014.
- Y. Yu, P. B. Luh, E. Litvinov, T. Zheng, F. Zhao, and J. Zhao, “Grid integration of distributed wind generation: A Markovian and interval approach,” submitted.

Thank you!

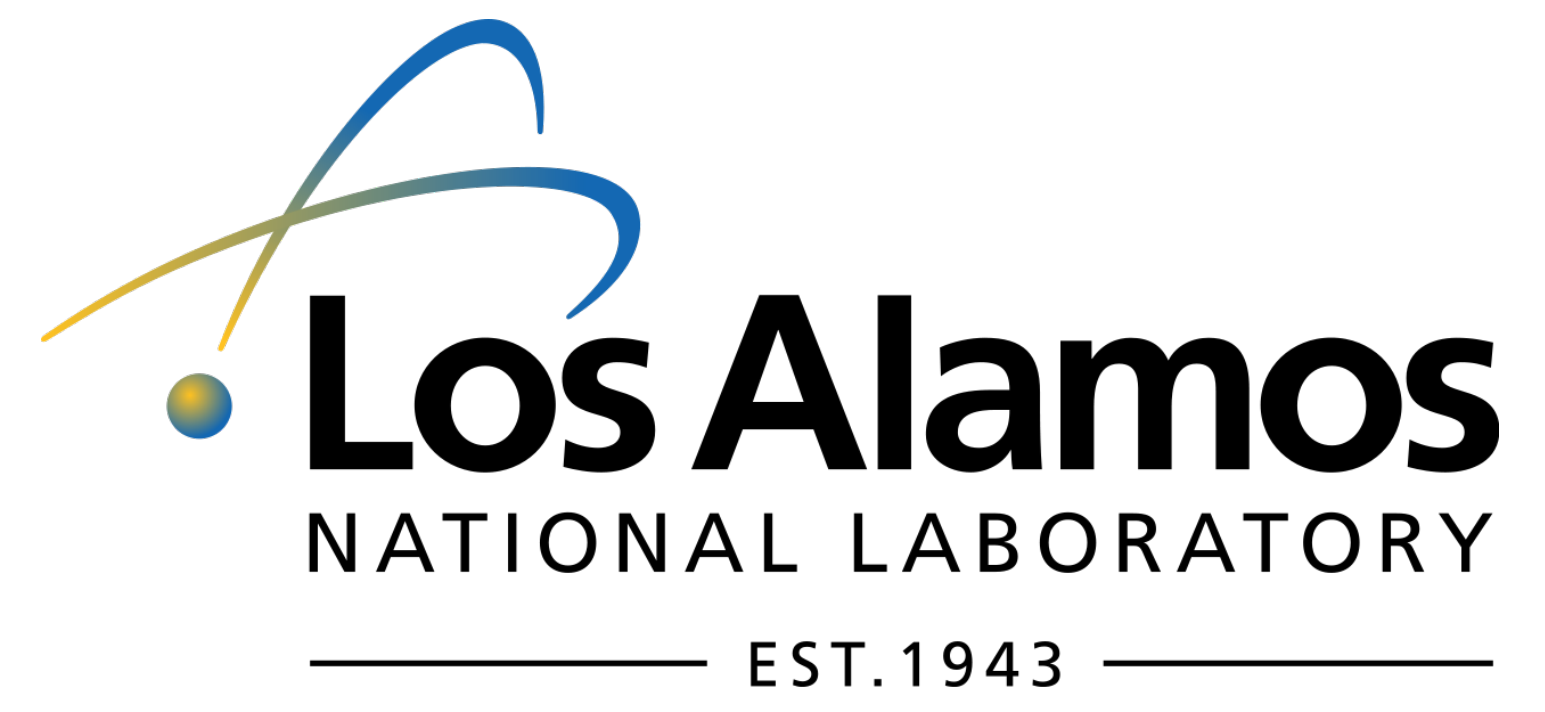


Designing Resilient Electrical Distribution Grids

Emre Yamangil, Russell Bent and Scott Backhaus

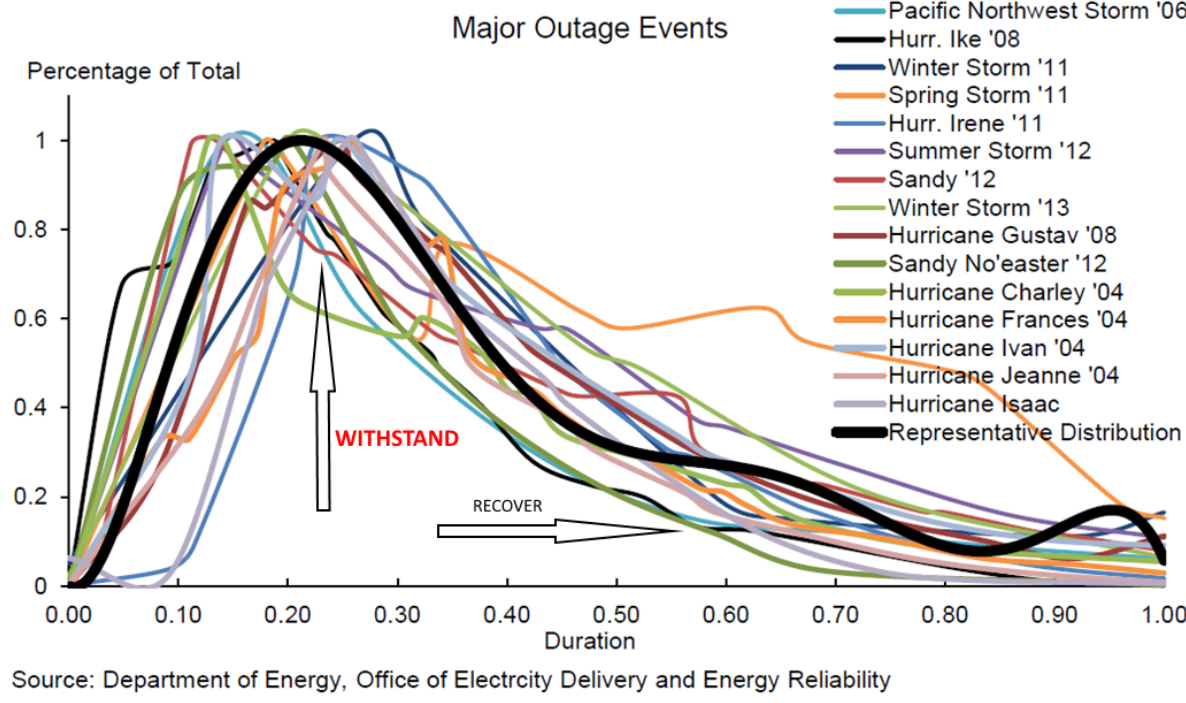
Rutgers University & Los Alamos National Laboratory

Grid Science Winter School & Conference, Jan. 12th



Presidential Policy Directive - Critical Infrastructure Security and Resilience

“The ability to prepare for and adapt to changing conditions and **withstand** and **recover** rapidly from disruptions. Resilience includes the ability to withstand and recover from deliberate attacks, accidents, or naturally occurring threats or incidents.”



A Simplified Model

Given a graph $G = (V, E)$ where V corresponds to node based upgrades (i.e. building facilities and microgrid generation capacity) and E corresponds to line based upgrades (i.e. building new lines, hardening lines and building switches) we want to find:

$$\begin{aligned} \min \quad & \text{Budget}(G') \\ \text{s.t.} \quad & G' \subseteq G \\ & T_s \subseteq G' \quad \forall s \in S \\ & T_s \in \text{Trees}(G) \quad \forall s \in S \\ & \text{CriticalDemand}(T_s) \geq \text{MinCriticalDemand} \quad \forall s \in S \\ & \text{TotalDemand}(T_s) \geq \text{MinTotalDemand} \quad \forall s \in S \end{aligned}$$

Algorithm 1: Greedy¹

input: A set of disasters S ;
1 for $s \in S$ **do**
2 $\sigma^s \leftarrow \text{Solve}(P'(s))$;
3 $\sigma^*(x) = \max\{\sigma^s(x) \mid \forall s \in S\}$, $\forall x \in \mathcal{X}$;
4 Update $\sigma^*(x_i)$ with switches to preserve feasibility;
5 return σ^*

Algorithm 2: Scenario Based Decomposition¹

input: A set of disasters S and let $S' = S_0$;
1 while $S \setminus S' \neq \emptyset$ **do**
2 $\sigma^* \leftarrow \text{Solve } P(S')$ exactly (SBD) or with VNS (SBVNDs);
3 $I \leftarrow \langle s_1, s_2, \dots, s_{|S \setminus S'|} \rangle$, $s \in S \setminus S' : l(P'(s_i, \sigma^*)) \geq l(P'(s_{i+1}, \sigma^*))$;
4 if $l(P'(I(0), \sigma^*)) \leq 0$ **then**
5 **return** σ^* ;
6 else
7 $S' \leftarrow S' \cup I(0)$;
8 return σ^*

Algorithm 3: Variable Neighborhood Search¹

input: σ' , MAXTIME, MAXRESTARTS and MAXITERATIONS;
1 Let $\sigma^{LP} \leftarrow \text{Solve}(P^{LP})$, $\sigma^* \leftarrow \sigma'$, $restart \leftarrow false$;
2 while $t < \text{MAXTIME}$ **and** $i < \text{MAXRESTARTS}$ **do**
3 $j \leftarrow 0$;
4 $n \leftarrow |x \in \mathcal{X} : |\sigma^*(x) - \sigma^{LP}(x)| \neq 0|$;
5 $J \leftarrow \langle \pi_1, \pi_2, \dots, \pi_{|J|} \rangle \in \mathcal{X} : |\sigma^*(\pi_i) - \sigma^{LP}(\pi_i)| \leq |\sigma^*(\pi_{i+1}) - \sigma^{LP}(\pi_{i+1})|$;
6 if $restart$ **then**
7 $i \leftarrow i + 1$;
8 $step \leftarrow \frac{4n}{d}$, $k = |\mathcal{X}| - step$;
9 $shuffle(J)$
10 else
11 $step \leftarrow \frac{n}{d}$, $k = |\mathcal{X}| - step$;
12 while $t < \text{MAXTIME}$ **and** $j \leq \text{MAXITERATIONS}$ **do**
13 $\sigma' \leftarrow \text{Solve}(P(\sigma^*, J(1, \dots, k)))$;
14 if $f(\sigma') < f(\sigma^*)$ **then**
15 $\sigma^* \leftarrow \sigma'$;
16 $i \leftarrow 0$;
17 $restart \leftarrow false$;
18 $j \leftarrow \text{MAXITERATIONS}$;
19 else
20 $j \leftarrow j + 1$;
21 $k = k - \frac{step}{2}$;
22 if $j > \text{MAXITERATIONS}$ **then**
23 $restart \leftarrow true$;
24 return σ^*

¹Yamangil, Bent, Backhaus (2015), Resilient Upgrade of Electrical Distribution Grids, in *proceedings of AAAI-15*, AAAI press.

Withstand

Develop new tools, methodologies, and algorithms to enable the design of resilient power distribution systems, using:

- ▶ asset hardening
 - ▶ system design
 - ▶ building new lines
 - ▶ building switches
 - ▶ building microgrid facilities
 - ▶ building microgrid generation capacity
- ⇒ binary decisions, mixed-integer programming.

Nomenclature

Parameters
 \mathcal{N} set of nodes (buses).
 \mathcal{E} set of edges (lines and transformers).
 \mathcal{S} set of disaster scenarios.
 \mathcal{D}_s set of edges that are inoperable during $s \in \mathcal{S}$.
 \mathcal{D}_s set of hardened edges that are inoperable during disaster $s \in \mathcal{S}$.
 c_{ij} cost to build a line between bus i and j . 0 if line already exists.
 κ_{ij} cost to build a switch on a line between bus i and j .
 ψ_{ij} cost to harden a line between bus i and j .
 $\zeta_{i,k}$ cost of generation capacity on phase k at bus i .
 α_i cost to build a generation facility at node i .
 Q_{ijk} line capacity between bus i and bus j on phase k .
 \mathcal{P}_{ij} set of phases for the line between bus i and bus j .
 \mathcal{P}_i set of phases allowed to consume or inject at bus i .
 β_{ij} parameter for controlling maximum flow variation between the phases.
 d_i demand for power at bus i for phase k .
 $G_{i,k}$ existing generation capacity on phase k at node i .
 $Z_{i,k}$ maximum amount of generation capacity on phase k that can be built at node i .
 \mathcal{C} the set of sets of nodes that includes a cycle.
 λ fraction of critical load that must be served.
 γ fraction of all load that must be served.
 \mathcal{L} set of buses whose load is critical.
Variables
 x_{ij} determines if line i, j is built.
 τ_{ij} determines if line i, j has a switch.
 t_{ij} determines if line i, j is hardened.
 $z_{i,k}$ determines the capacity for generation on phase k at node i .
 u_i determines the generation capacity built at node i .
 x_{ij}^s determines if line i, j is used during disaster s .
 τ_{ij}^s determines if switch i, j is used during disaster s .
 t_{ij}^s determines if line i, j is hardened during disaster s .
 $z_{i,k}^s$ determines the capacity for generation on phase k at bus i during disaster s .
 u_i^s indicates if the generation capacity is used at node i during disaster s .
 $g_{i,k}^s$ generation produced for bus i on phase k during disaster s .
 $l_{i,k}^s$ load delivered at bus i on phase k during disaster s .
 $y_{ij,k}^s$ determines if the j th load at bus i is served or not during disaster s .
 $f_{ij,k}^s$ flow between bus i and bus j on phase k during disaster s .
 τ_{ij}^s determines if at least one edge between i and j is used during disaster s .
 $x_{ij,0}^s$ determines if there exists flow on line i, j from j to i , during disaster s .
 $x_{ij,1}^s$ determines if there exists flow on line i, j from i to j , during disaster s .

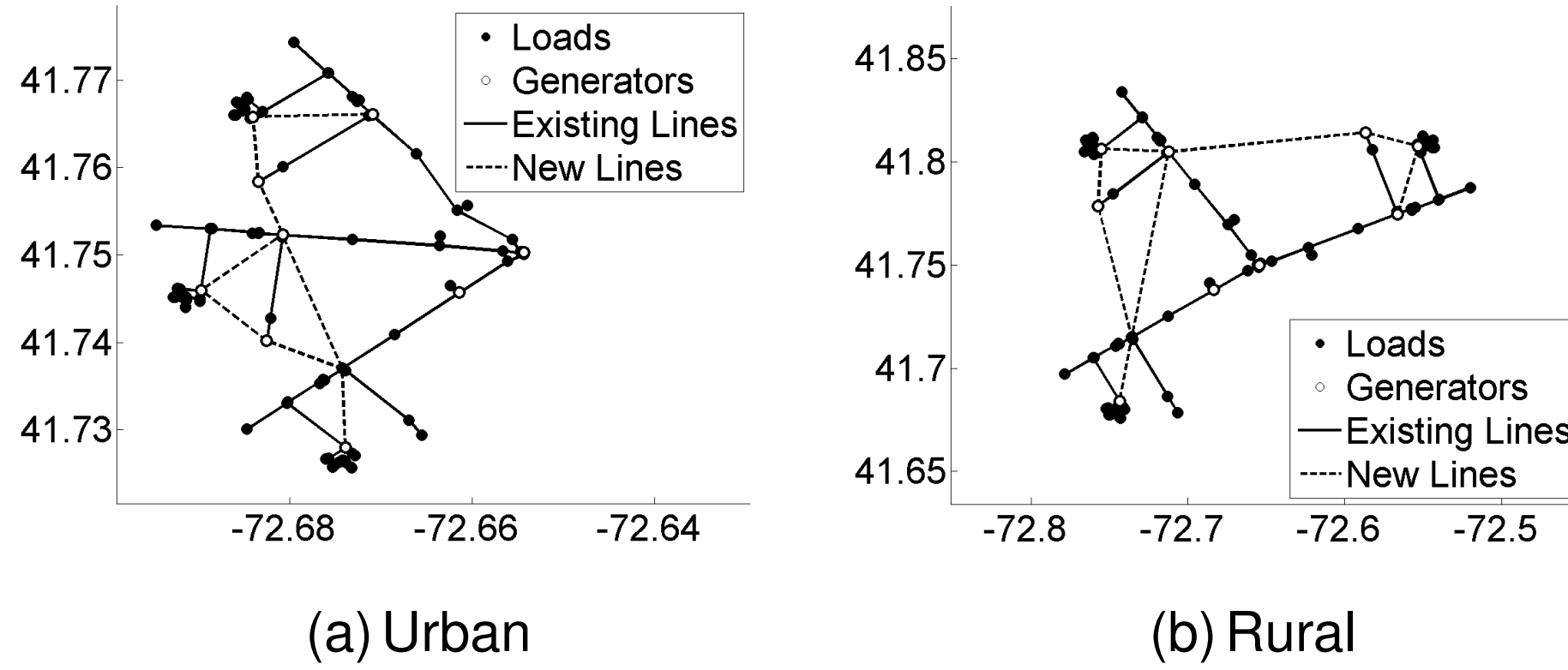
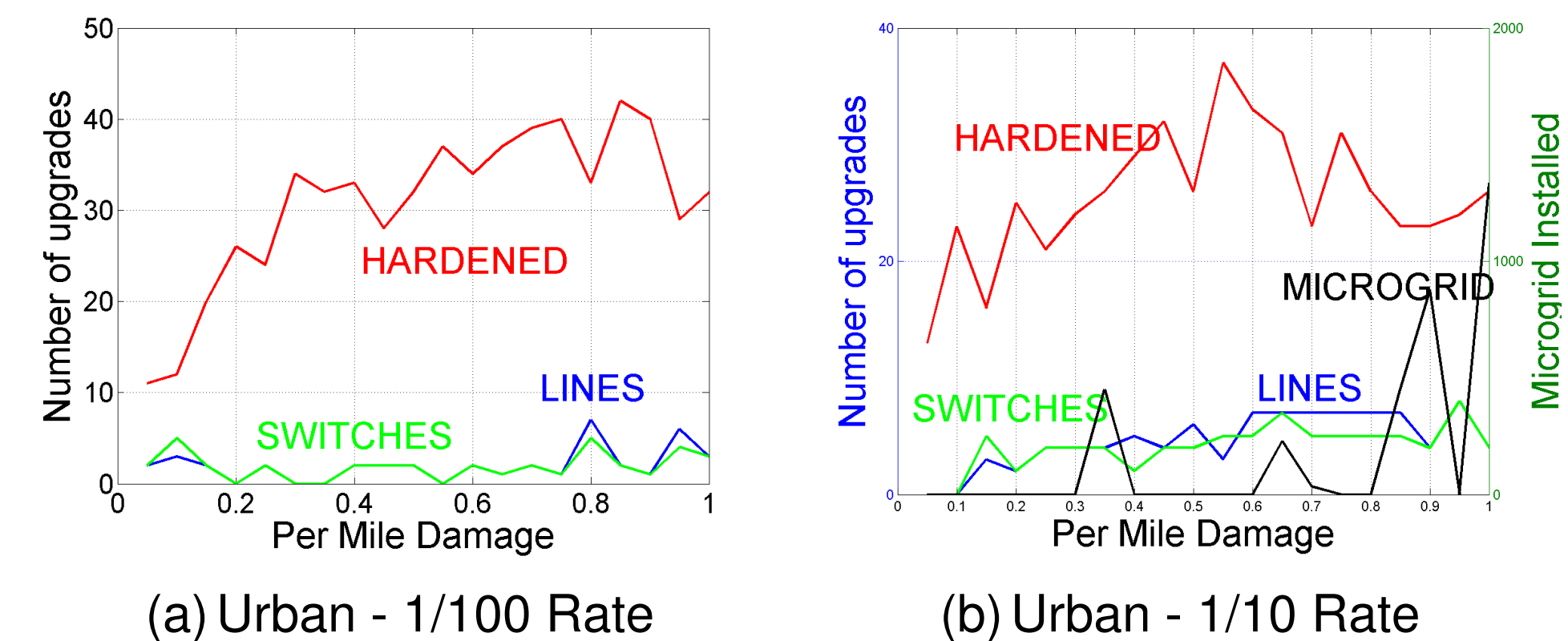


Figure : Each problem contains three copies of the IEEE 34 system to mimic situations where there are three normally independent distribution circuits that could support each other during extreme events. These problems include 100 scenarios, 109 nodes, 118 possible generators, 204 loads, and 148 edges, resulting in problems with **> 90k** binary variables. The cost of single and three phase underground lines is between **\$40k** and **\$1500k** per mile and we adopt the cost of **\$100k** per mile and **\$500k** per mile, respectively. The cost of single and three phase switches is estimated to be **\$10k** and **\$15k**, respectively. Finally, the installed cost of natural gas-fired CHP in a microgrid is estimated to be **\$1500k** per MW.

Urban, Hardened lines are not damageable (a)						
	CPLEX		Greedy	SBD		SBVNDs
	CPU	OBJ	OBJ	CPU	OBJ	CPU OBJ
10%	19984.7	322.9	1044.5	465.8	322.9	289.9 353.7
25%	166352	635.4	1643.5	8028.3	635.4	811.4 635.4
50%	TO	X	2021.2	2840.7	647.7	791.3 647.7
75%	TO	X	1874.2	991.1	652.1	692.5 652.1
100%	TO	X	1934.4	712.7	654.1	662.5 654.1

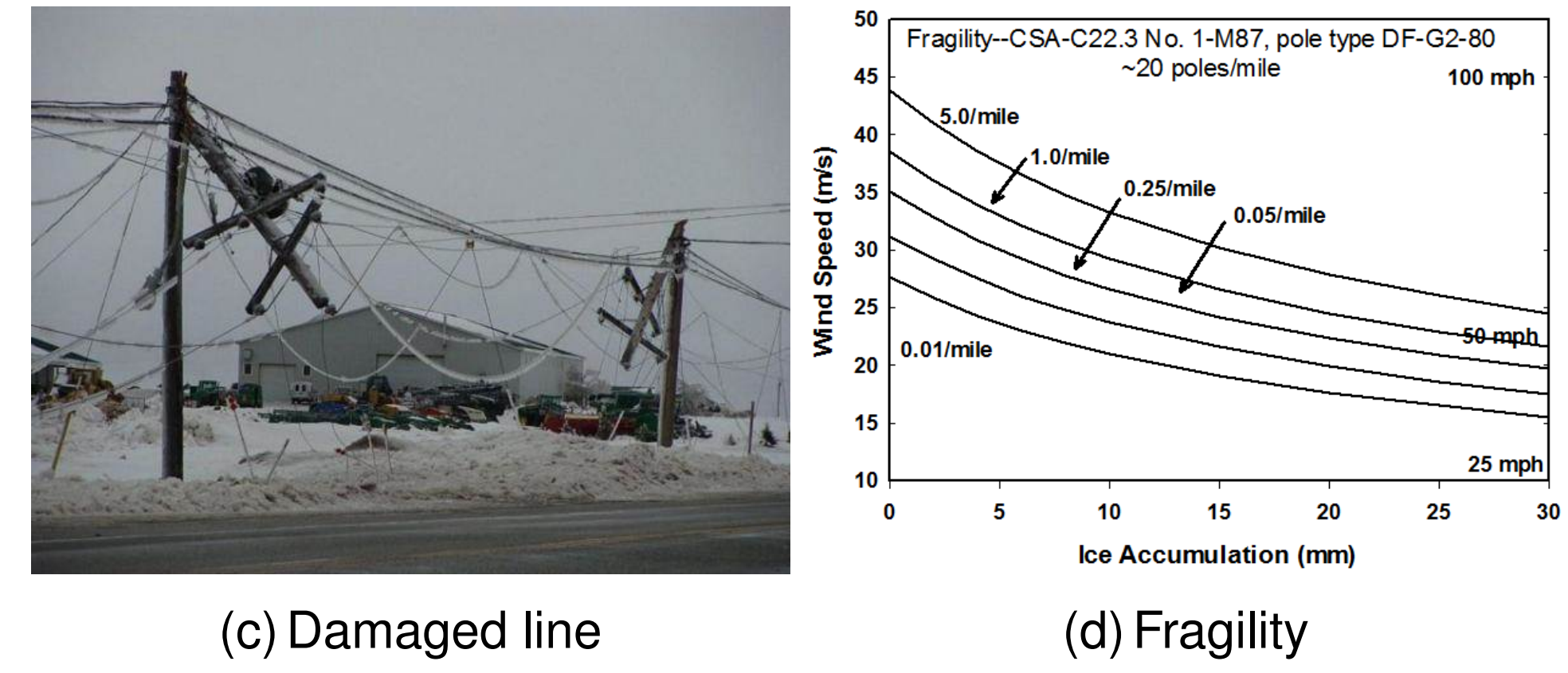
Urban, Hardened lines are damaged at a $\frac{1}{100}$ rate (c)						
	CPLEX		Greedy	SBD		SBVNDs
	CPU	OBJ	OBJ	CPU	OBJ	CPU OBJ
10%	159166	445.8	1061.7	2232.9	445.8	2721.3 476.5
25%	TO	X	1441.9	14299.2	662.9	2994.7 701.5
50%	TO	X	1571.2	2848.7	646.0	1917.7 760.2
75%	TO	X	1787.3	16040.6	687.6	1481.4 687.6
100%	TO	X	2744.8	24270.3	1320.5	2157.5 1330.5

Urban, Hardened lines are damaged at a $\frac{1}{10}$ rate (e)						
	CPLEX		Greedy	SBD		SBVNDs
	CPU	OBJ	OBJ	CPU	OBJ	CPU OBJ
10%	TO	X	859.1	5265.1	460.8	2505.7 594.1
25%	TO	X	1742.2	12530.3	961.2	2843.2 961.2
50%	TO	X	3133.8	34822.7	1417.2	3363.5 1555.2
75%	TO	X	3472.0	TO	X	7486.5 1894.2
100%	TO	X	10479.1	TO	X	32289.8 7959.4



Scenario Definition

We assume each scenario can be associated to a subset of the lines of the power distribution system that are inoperable:



Resilient Distribution Grid Design

$$\begin{aligned} \min \quad & \sum_{ij \in \mathcal{E}} c_{ij} x_{ij} + \sum_{ij \in \mathcal{E}} \kappa_{ij} \tau_{ij} + \sum_{ij \in \mathcal{E}} \psi_{ij} t_{ij} \\ & + \sum_{i \in \mathcal{N}} \alpha_i u_i + \sum_{i \in \mathcal{N}, k \in \mathcal{P}_i} \zeta_{i,k} z_{i,k} \\ \text{s.t.} \quad & x_{ij}^s \leq x_{ij} \quad \forall ij \in \mathcal{E}, s \in \mathcal{S} \\ & \tau_{ij}^s \leq \tau_{ij} \quad \forall ij \in \mathcal{E}, s \in \mathcal{S} \\ & t_{ij}^s \leq t_{ij} \quad \forall ij \in \mathcal{E}, s \in \mathcal{S} \\ & z_{i,k}^s \leq z_{i,k} \quad \forall i \in \mathcal{N}, k \in \mathcal{P}_i, s \in \mathcal{S} \\ & u_i^s \leq u_i \quad \forall i \in \mathcal{N}, s \in \mathcal{S} \\ & z_{i,k} \leq M_{i,k} u_i \quad \forall i \in \mathcal{N}, k \in \mathcal{P}_i \\ & (x^s, \tau^s, t^s, z^s, u^s) \in \mathcal{Q}(s) \quad \forall s \in \mathcal{S} \\ & x, \tau, t, u \in \{0, 1\} \end{aligned}$$

Minimize budget

1st stage: construction

2nd stage: assets in use flow delivery

Set of Feasible Distribution Networks

$$\begin{aligned} \mathcal{Q}(s) = \{x^s, \tau^s, t^s, z^s, u^s : \\ - x_{ij,0}^s Q_{ijk} \leq f_{ij,k}^s \leq x_{ij,1}^s Q_{ijk} \quad \forall ij \in \mathcal{E}, k \in \mathcal{P}_{ij} \\ x_{ij,0}^s + x_{ij,1}^s \leq x_{ij}^s \quad \forall ij \in \mathcal{E} \\ (\tau_{ij}^s - 1) Q_{ijk} \leq f_{ij,k}^s \leq (1 - \tau_{ij}^s) Q_{ijk} \quad \forall ij \in \mathcal{E}, k \in \mathcal{P}_{ij} \\ \sum_{k \in \mathcal{P}_{ij}} f_{ij,k}^s \leq \sum_{k \in \mathcal{P}_{ij}} f_{ij,k}^s \quad \forall ij \in \mathcal{E}, k' \in \mathcal{P}_{ij} \\ \frac{\sum_{k \in \mathcal{P}_{ij}} f_{ij,k}^s}{|P_{ij}|} \leq f_{ij,k'}^s \leq \frac{\sum_{k \in \mathcal{P}_{ij}} f_{ij,k}^s}{|P_{ij}|(1 + \beta_{ij})} \quad \forall ij \in \mathcal{E}, k' \in \mathcal{P}_{ij} \\ x_{ij}^s = t_{ij}^s \leq \begin{cases} 0 & \text{if } ij \in \mathcal{D}'^s \\ 1 & \text{else} \end{cases} \quad \forall ij \in \mathcal{D}_s \\ f_{i,k}^s = \sum_{j=0}^{n_i} y_{ij,k}^s d_{i,j,k}^s \quad \forall i \in \mathcal{N}, k \in \mathcal{P}_i \\ 0 \leq g_{i,k}^s \leq z_{i,k}^s + G_{i,k} \quad \forall i \in \mathcal{N}, k \in \mathcal{P}_i \\ g_{i,k}^s - l_{i,k}^s - \sum_{j \in \mathcal{N}} f_{ij,k}^s = 0 \quad \forall i \in \mathcal{N}, k \in \mathcal{P}_i \\ 0 \leq z_{i,k}^s \leq Z_{i,k} u_i \quad \forall i \in \mathcal{N}, k \in \mathcal{P}_i \\ \sum_{ij \in \mathcal{E}(C)} (x_{ij}^s - \tau_{ij}^s) \leq |V| - 1 \quad \forall C \in \mathcal{C} \\ \tau_{ij}^s \leq x_{ij}^s \quad \forall ij \in \mathcal{E} \\ \sum_{i \in \mathcal{L}, k \in \mathcal{P}_i} l_{i,k}^s \geq \lambda \sum_{i \in \mathcal{L}, k \in \mathcal{P}_i} d_{i,k} \\ \sum_{i \in \mathcal{N} \setminus \mathcal{L}, k \in \mathcal{P}_i} l_{i,k}^s \geq \gamma \sum_{i \in \mathcal{N} \setminus \mathcal{L}, k \in \mathcal{P}_i} d_{i,k} \\ x^s, y^s, \tau^s, u^s, l^s \in \{0, 1\} \} \end{aligned}$$

3-phase real flow

Modeled as multicommodity flow with phase variation

Hardened lines can still be damaged

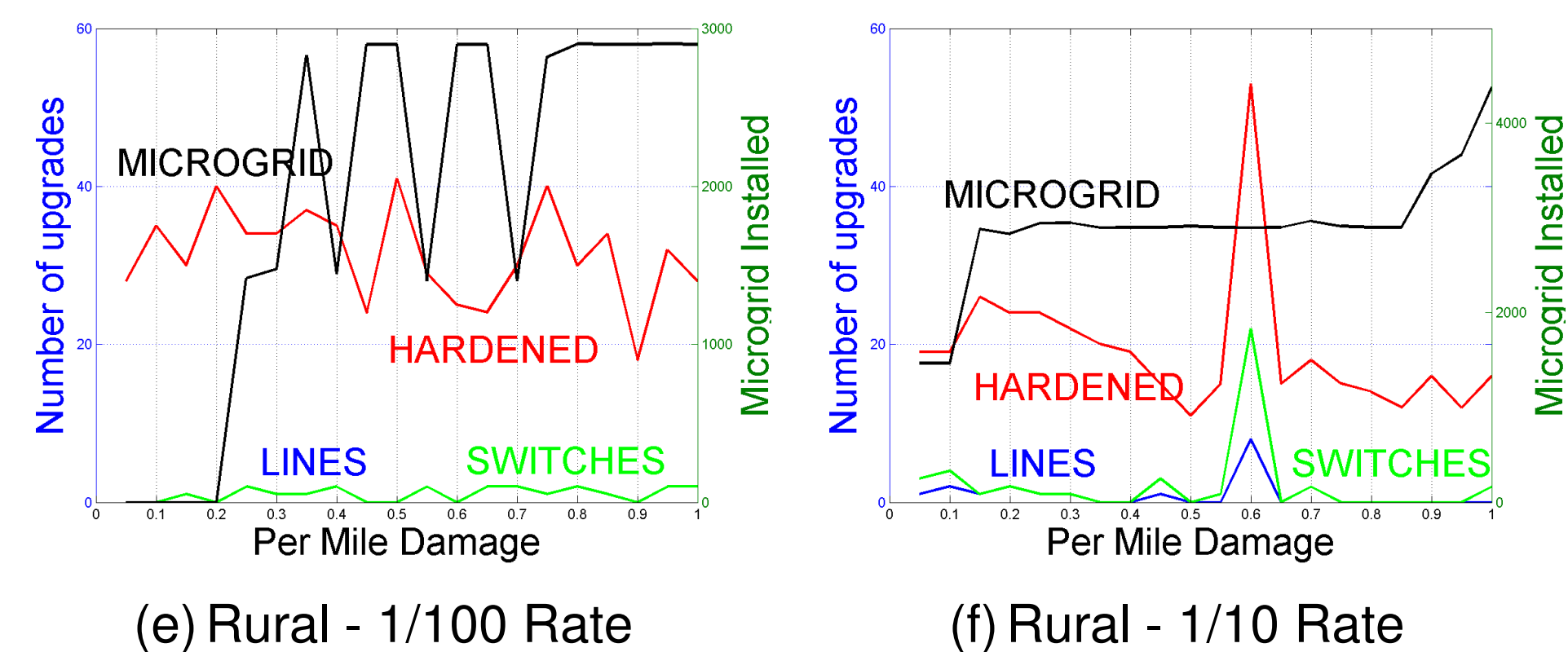
Distribution network ⇒ tree

Minimum service requirement as resilience criteria

Rural, Hardened lines are not damageable (b)						
	CPLEX		Greedy	SBD		SBVNDs
	CPU	OBJ	OBJ	CPU	OBJ	CPU OBJ
10%	33083.5	2337.0	3274.8	1837.9	2337.0	503.3 2337.0
25%	32170.8	2390.3	3427.6	571.0	2390.3	457.8 2390.3
50%	20840.3	2397.6	3449.9	471.2	2397.6	421.2 2397.6
75%	15556.1	2400.4	3452.7	337.5	2400.4	299.8 2400.4
100%	17225.9	2400.6	2780.6	385.8	2400.6	346.9 2400.6

Rural, Hardened lines are damaged at a $\frac{1}{100}$ rate (d)						
	CPLEX		Greedy	SBD		SBVNDs
	CPU	OBJ	OBJ	CPU	OBJ	CPU OBJ
10%	77947.9	2363.0	3375.4	759.0	2363.0	576.9 2363.0
25%	TO	X	8238.6	TO	X	919.4 6744.3
50%	TO	X	12336.0	TO	X	9288.9 4361.8
75%	TO	X	23099.5	TO	X	23142.6 11500.0
100%	TO	X	16600.7	TO	X	5879.5 9797.3

Rural, Hardened lines are damaged at a $\frac{1}{10}$ rate (f)						
	CPLEX		Greedy	SBD		SBVNDs
	CPU	OBJ	OBJ	CPU	OBJ	CPU OBJ
10%	TO	X	7503.3	141718.0	4325.9	7756.8 4424.8
25%	TO	X	18021.3	TO	X	21993.5 7371.9
50%	TO	X	28865.0	TO	12017.7	74729.0 12031.2
75%	TO	X	31887.0	TO	13522.2	107165.0 13500.8
100%	TO	X	32901.9	TO	16794.4	114354.0 16778.2





Lyapunov Functions Family Approach to Transient Stability Assessment



Thanh Long Vu and Konstantin Turitsyn
Massachusetts Institute of Technology

MOTIVATIONS

1. Emerging technologies are changing the way power grids operate
2. The existing planning and operation computational techniques have to be reassessed
3. Variations in the grids (e.g. mechanical torques, topology) result in different operating conditions

PROBLEMS

We consider two stability assessment problems of power grids:

Transient stability: Estimate the region of attraction of the stable equilibrium point $\delta^* = [\delta_1^*, \dots, \delta_n^*, 0, \dots, 0]^T$, i.e. the set of initial conditions $\{\delta_k(0), \dot{\delta}_k(0)\}_{k=1}^n$ starting from which the system (1)-(2) converges to δ^* .

Robust transient stability: Certify the stability of the system (1)-(2), where the mechanical torques P_k are varying such that the stable equilibrium point δ^* is in the polytope Θ defined by the inequalities $|\delta_{kj}^*| \leq \Delta_{kj}$.

CONTRIBUTIONS

1. Introduced the LFF approach to certify the transient stability of structure-preserving multimachine power grids
2. This approach is applicable to lossy power grids, which is impossible by the standard energy methods
3. Presented optimization and LMI-based techniques to explicitly construct the stability certificates and to adapt the Lyapunov functions to initial states
4. Posed a new control problem of stability assessment for systems with unknown equilibria
5. Applied the LFF approach to uncertain power grids with unknown equilibrium points and provided robust stability certificates

FUTURE DIRECTIONS

1. Extend the LFF stability assessment approach to more realistic models of generators, loads, and transmission network:

- Structure-preserving models with reactive powers: extending the nonlinearity F
- Higher-order models of generators with voltage dynamics, and higher-order loads

2. Design optimization algorithms to improve computational efficiency

STRUCTURE PRESERVING DYNAMICAL SWING EQUATIONS

Consider the structure-preserving model of power grids described by the swing equations:

$$(\mathcal{G}) \quad m_k \ddot{\delta}_k + d_k \dot{\delta}_k = P_{m_k} - V_k^2 G_k - \sum_{j \in \mathcal{N}_k} V_k V_j B_{kj} \sin(\delta_k - \delta_j), \quad k = 1, \dots, m \quad (1)$$

$$(\mathcal{L}) \quad d_k \dot{\delta}_k = -P_{d_k}^0 - \sum_{j \in \mathcal{N}_k} V_k V_j B_{kj} \sin(\delta_k - \delta_j), \quad k = m+1, \dots, n \quad (2)$$

The operating condition is characterized by the angle differences $\delta_{kj}^* = \delta_k^* - \delta_j^*$ satisfying:

$$\sum_{j \in \mathcal{N}_k} V_k V_j B_{kj} \sin \delta_{kj}^* = P_k, \quad k = 1, \dots, n \quad (3)$$

LFF APPROACH

Nonlinearity separation and bounding

$$\dot{x} = Ax - BF(Cx) \quad (4)$$

$$x = [\delta_1, \dots, \delta_m, \dot{\delta}_1, \dots, \dot{\delta}_m, \delta_{m+1}, \dots, \delta_n]^T$$

$$F(Cx) = [(\sin \delta_{kj} - \sin \delta_{kj}^*)]_{\{k,j\} \in \mathcal{E}}^T$$

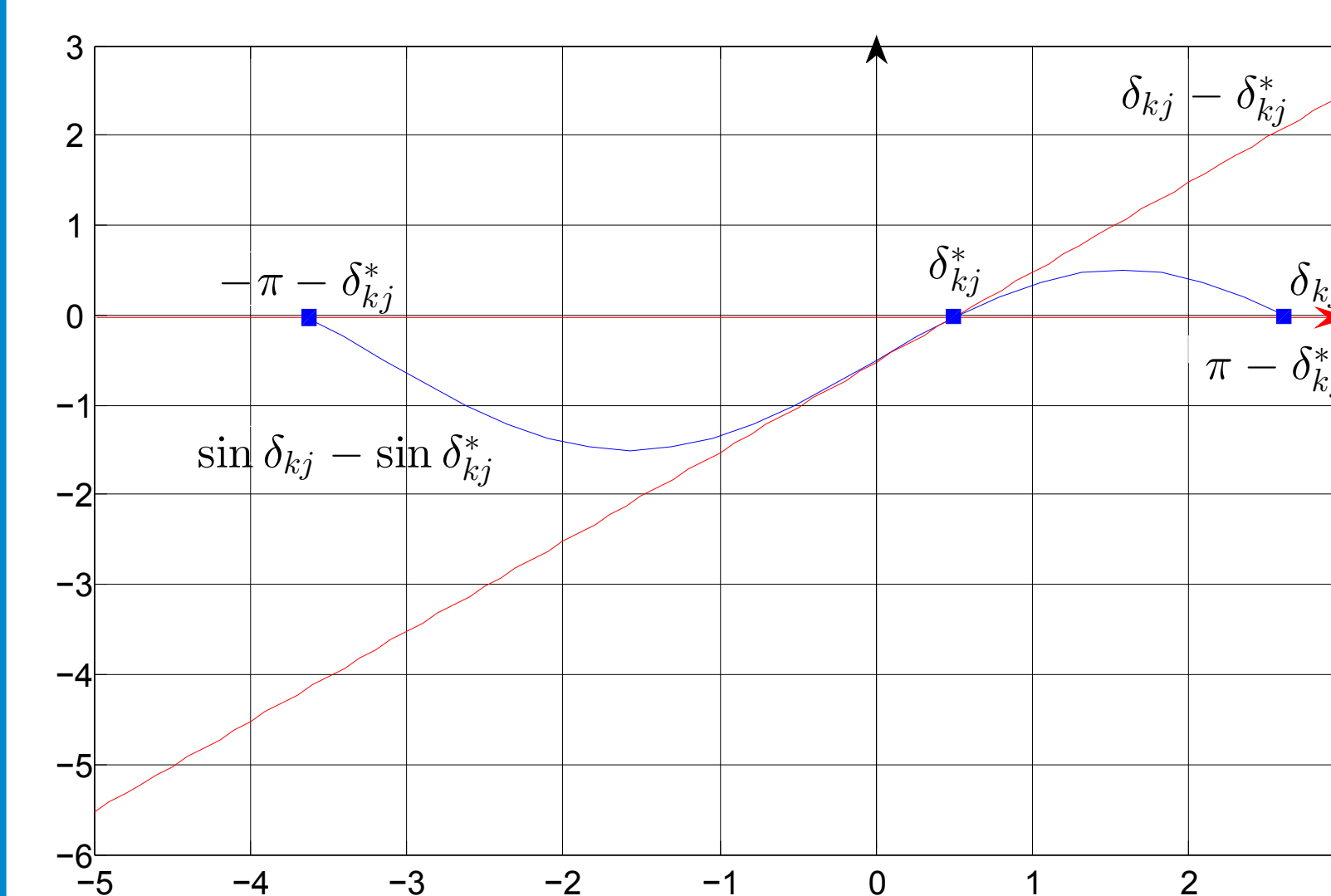


FIG. 1: Linear bounding of the nonlinear couplings

Lyapunov Functions Family

$$V(x) = \frac{1}{2} x^T Q x - \sum K_{k,j} (\cos \delta_{kj} + \delta_{kj} \sin \delta_{kj}^*)$$

where Q, K, H are solutions of the LMIs:

$$\begin{bmatrix} A^T Q + Q A & R \\ R^T & -2H \end{bmatrix} \leq 0, \quad (5)$$

with $R = QB - C^T H - (KCA)^T$.

Then, $\dot{V}(x) \leq 0$ for any state x stays within the polytope $\mathcal{P} := \{x : |\delta_{kj} + \delta_{kj}^*| \leq \pi\}$.

Adaptation to Initial States

Let ϵ be a positive constant.

Step 1: Find $Q^{(1)}, K^{(1)}, H^{(1)}$ by solving (5).

Step n : Find $Q^{(n)}, K^{(n)}, H^{(n)}$ by solving the following LMIs:

$$\begin{bmatrix} A^T Q^{(n)} + Q^{(n)} A & R^{(n)} \\ (R^{(n)})^T & -2H^{(n)} \end{bmatrix} \leq 0,$$

$$V^{(n)}(x_0) \leq V_{min}^{(n-1)} - \epsilon$$

Once infeasible, ϵ is replaced by $\epsilon/2$.

REFERENCES

- [1] T. L. Vu, K. Turitsyn. Lyapunov Functions Family Approach to Transient Stability Assessment. *IEEE Transactions on Power Systems*, in revision.
- [2] T. L. Vu, K. Turitsyn. Synchronization Stability of Lossy and Uncertain Power Grids. *2015 American Control Conference*, accepted.
- [3] T. L. Vu, K. Turitsyn. Geometry-based Estimation of Stability Region for a Class of Structure Preserving Power Systems. *2015 PES General Meeting*, in review.

RESULTS

Let $V_{min} := \min_{x \in \partial \mathcal{P}^{out}} V(x)$. Then, the set $\mathcal{R} := \{x \in \mathcal{P} : V(x) < V_{min}\}$ is invariant, and an estimate of stability region of the SEP δ^* .

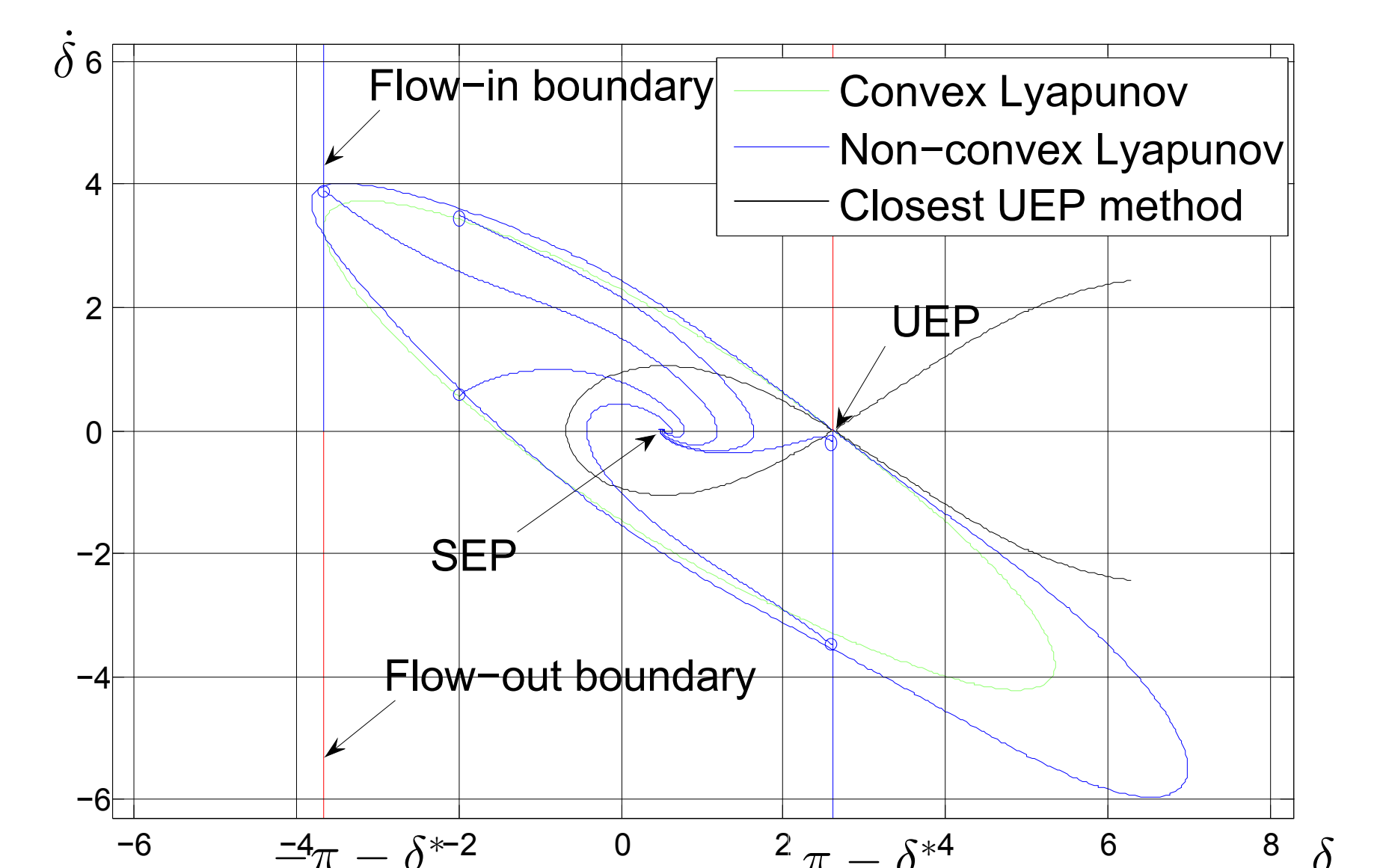


FIG. 2: Stability region estimates are intersections of the Lyapunov function sublevel sets and \mathcal{P}

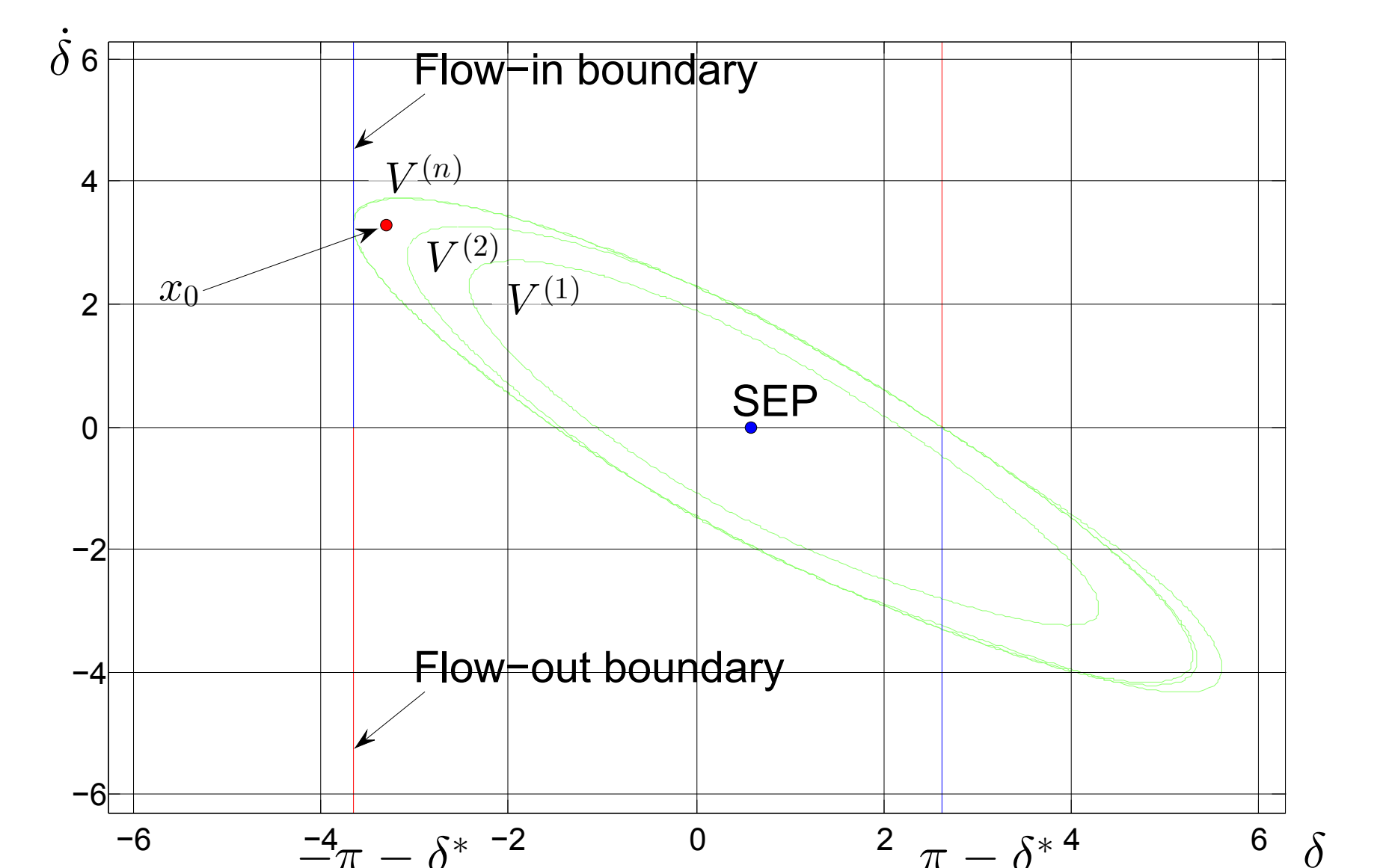


FIG. 3: Adaptation of the Lyapunov functions to x_0

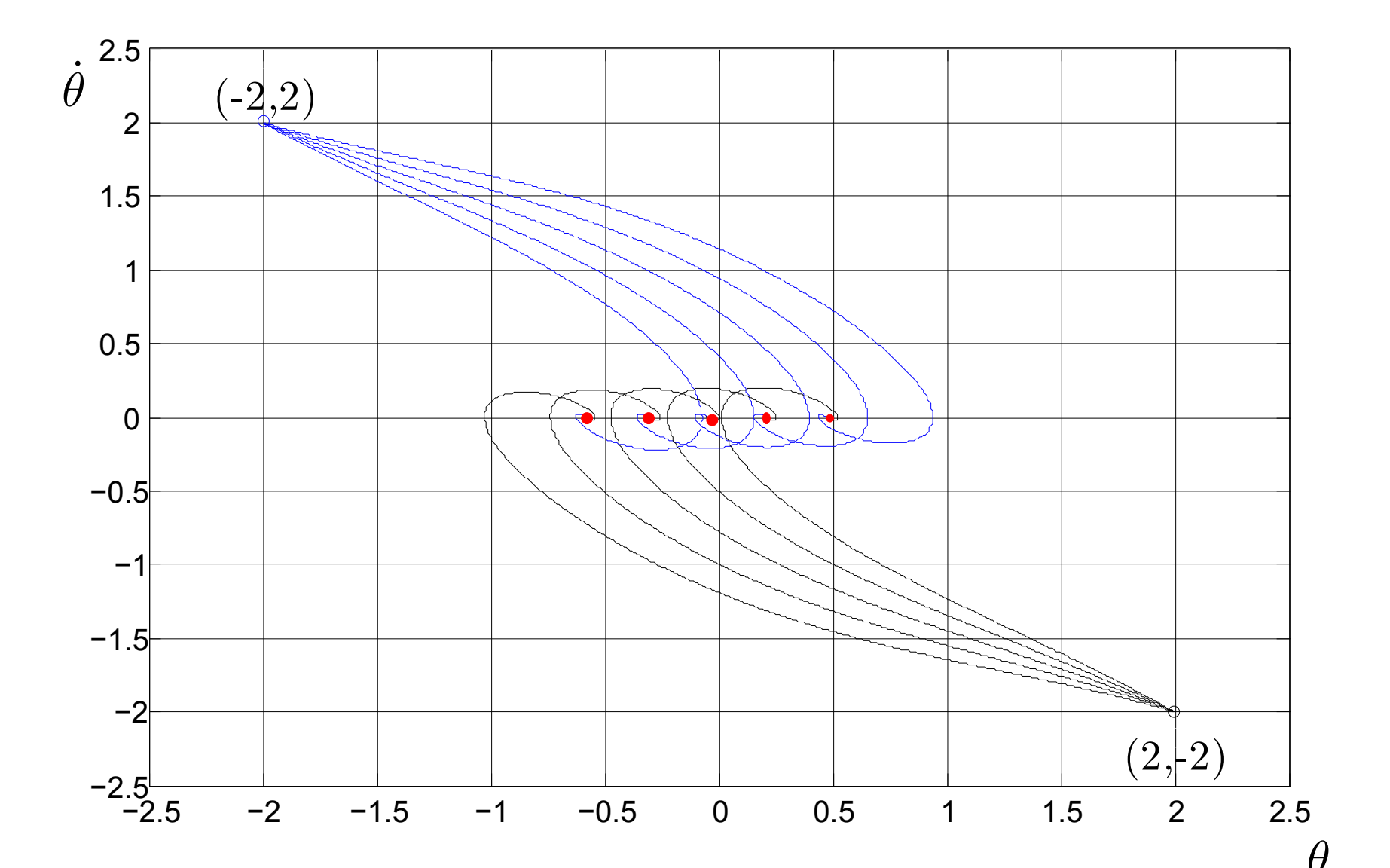


FIG. 4: Robust stability of $\{\delta_0 = -2, \dot{\delta}_0 = 2\}$ when δ^* is in the set $-\pi/6 - 0.05 \leq \delta^* \leq \pi/6 - 0.05$

ACKNOWLEDGEMENT

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Security Constrained Optimal Power Flow with Distributionally Robust Chance Constraints

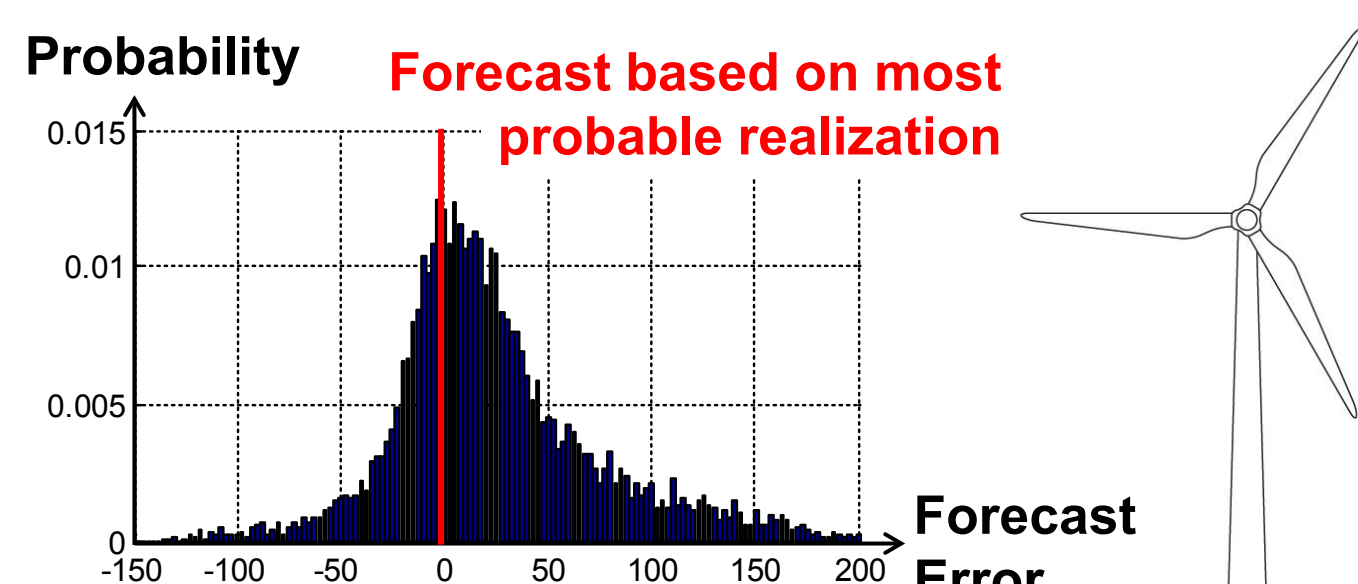
Line Roald, Frauke Oldewurtel*, Bart Van Parys°, Göran Andersson**
* Power Systems Laboratory and °Automatic Control Laboratory, ETH Zurich



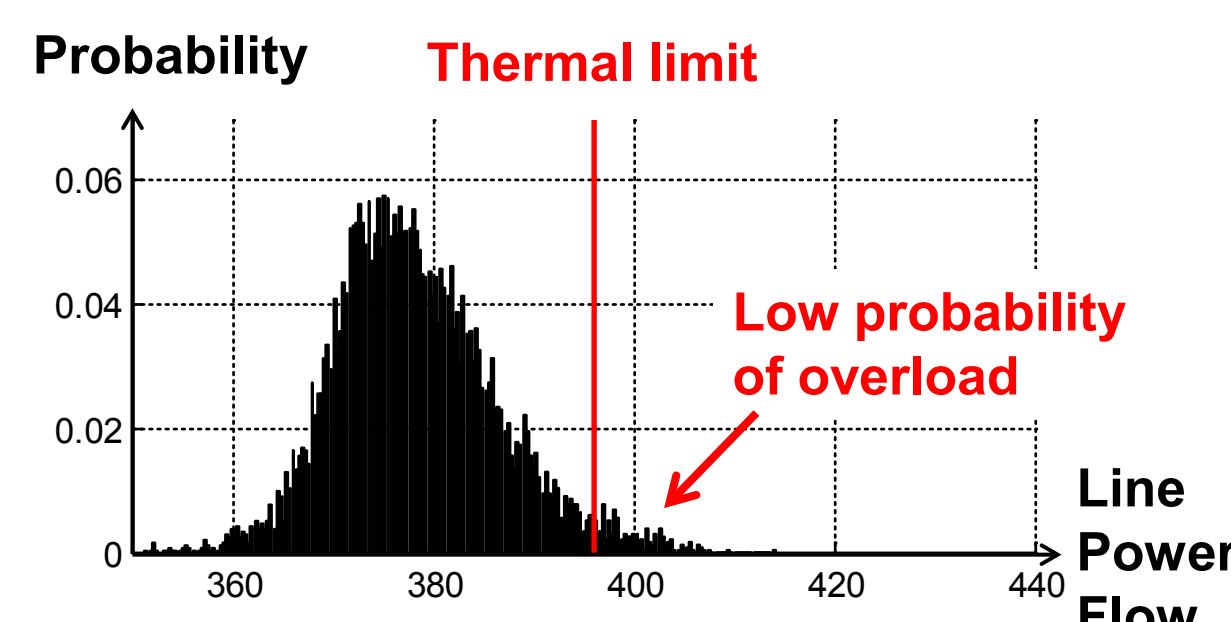
PROBLEM: Uncertain power injections → uncertain power flows

Uncertainty from

- Renewables
- Market liberalization (intra-day trading)



GOAL: Keep the system operation N-1 secure despite uncertainty



Use *chance constrained optimal power flow* to keep the *probability of line overload* below acceptable values

1. CHANCE CONSTRAINED OPTIMAL POWER FLOW

- Chance constraints reflect the probability of constraint violation
- Optimal power flow formulation based on DC power flow
- If a violation occurs, additional remedial actions are required from the system operator in real-time

CHANCE CONSTRAINT FOR POST-CONTINGENCY LINE FLOW

Scheduled power flow + change due to outage Change due to RES fluctuations Desired confidence level

$$\mathbb{P}(A^i P_{inj}^i + D^i \delta P_{inj} \leq P_{ij}^{max}) \geq 1 - \varepsilon$$

P_{inj}	Scheduled in-feeds	δP_{inj}	Uncertain in-feeds
A^i	System topology	μ	Mean vector
D^i	Influence of RES fluctuations	Σ	Covariance matrix
P_{ij}^{max}	Line flow limit	ε	Accepted violation prob.

2. ANALYTIC REFORMULATION OF THE CHANCE CONSTRAINTS

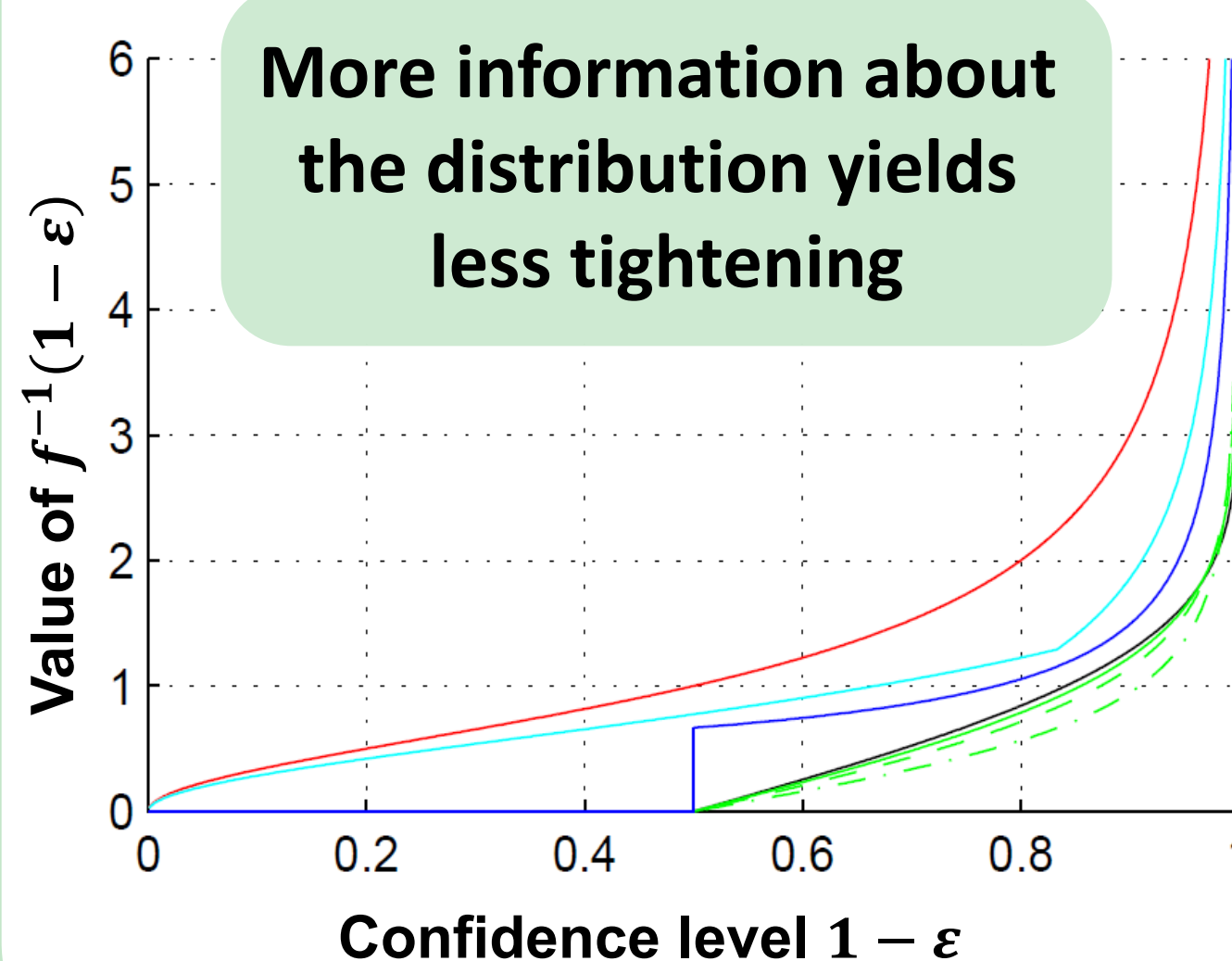
- + Influence of each uncertainty source is traceable
- + Deterministic solution (not dependent on the choice of samples)
- Only applicable when D^i is constant (linear program) or linearly in the decision variables (SOCP)

REFORMULATED CONSTRAINT

$$A^i P_{inj}^i \leq P_{ij}^{max} - f^{-1}(1 - \varepsilon) \|D^i \Sigma^{1/2}\|_2 - D^i \mu$$

3. $f^{-1}(1 - \varepsilon)$ DEPENDS ON (UNKNOWN) DISTRIBUTION OF δP_{inj}

More information about the distribution yields less tightening



Exact reformulation if distribution is known and elliptical:

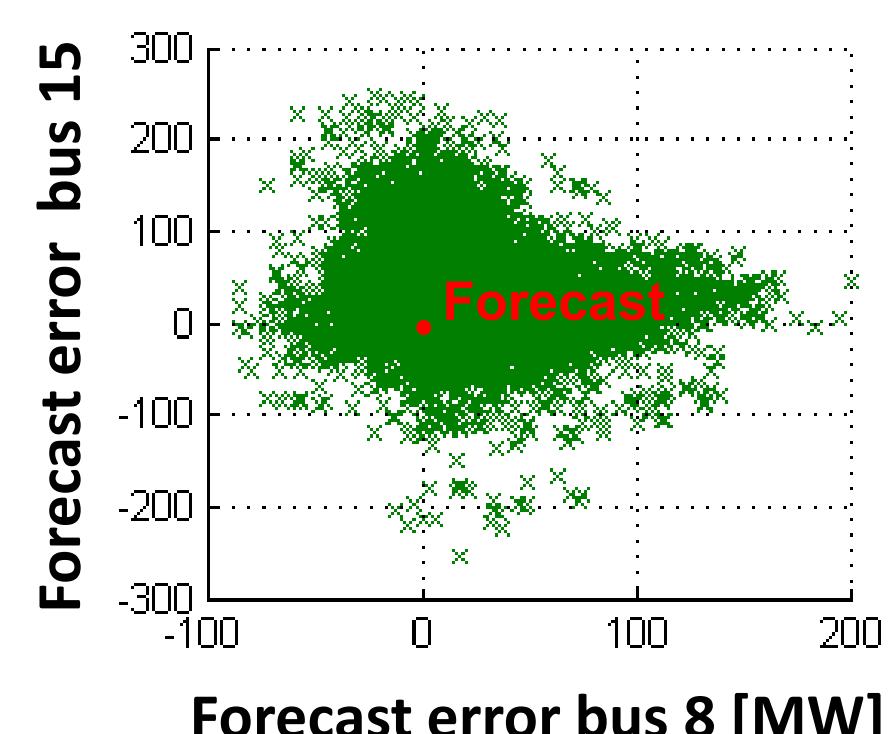
- normal distribution
- t distribution

Distributionally robust constraints if distribution is partially known:

- Chebyshev (known μ & Σ)
- Unimodal with known μ & Σ
- Symmetric, unimodal with known μ & Σ

CASE STUDY: IEEE RTS 96 WITH UNCERTAIN IN-FEEDS

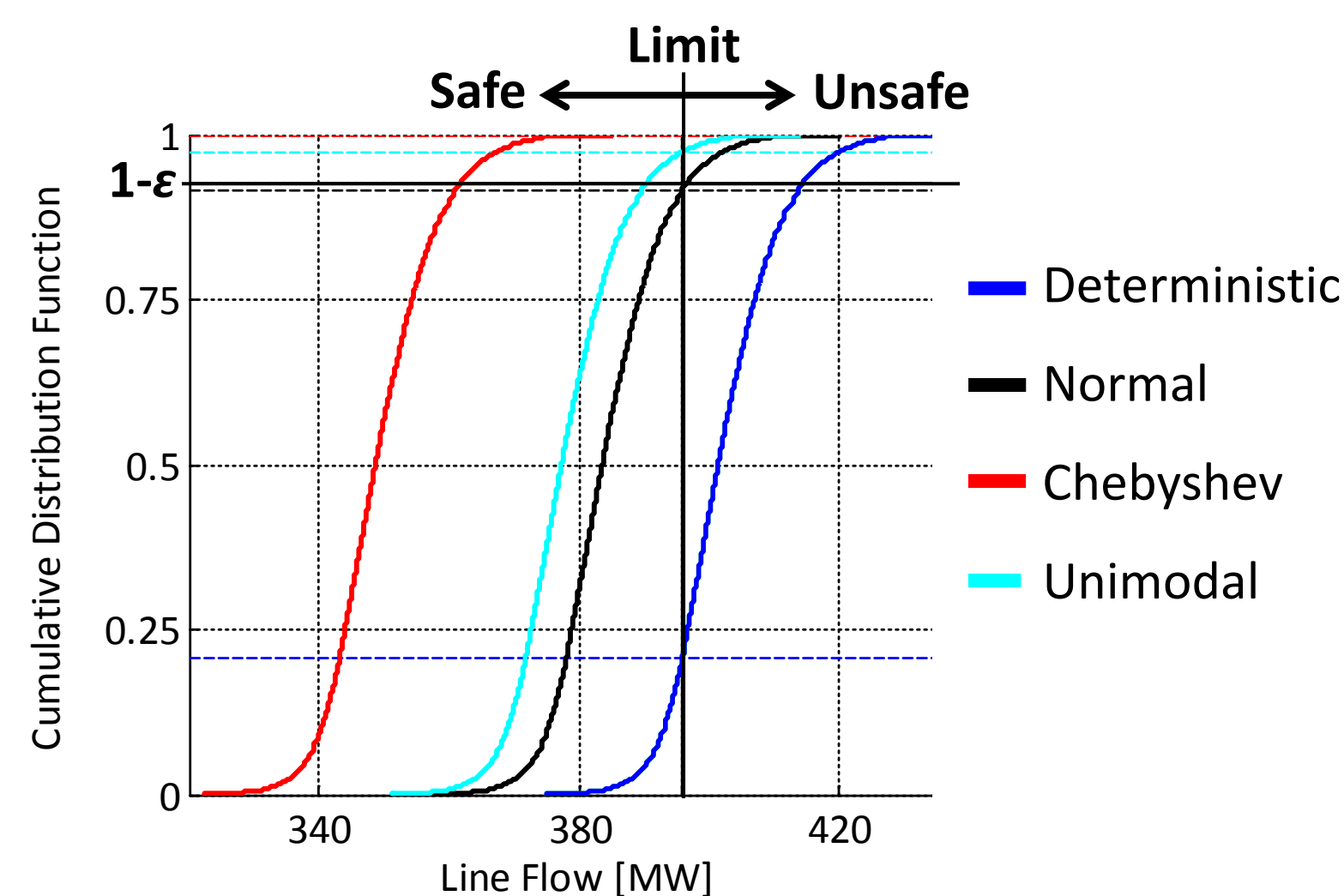
- Two uncertain in-feeds (bus 8, 15)
- μ, Σ based on samples of historical data from APG
- **Not normally distributed!**
- Accepted violation probability: $\varepsilon = 0.075$
- Different assumptions on probability distribution of δP_{inj}



POWER FLOW ON LINE 15 – 16

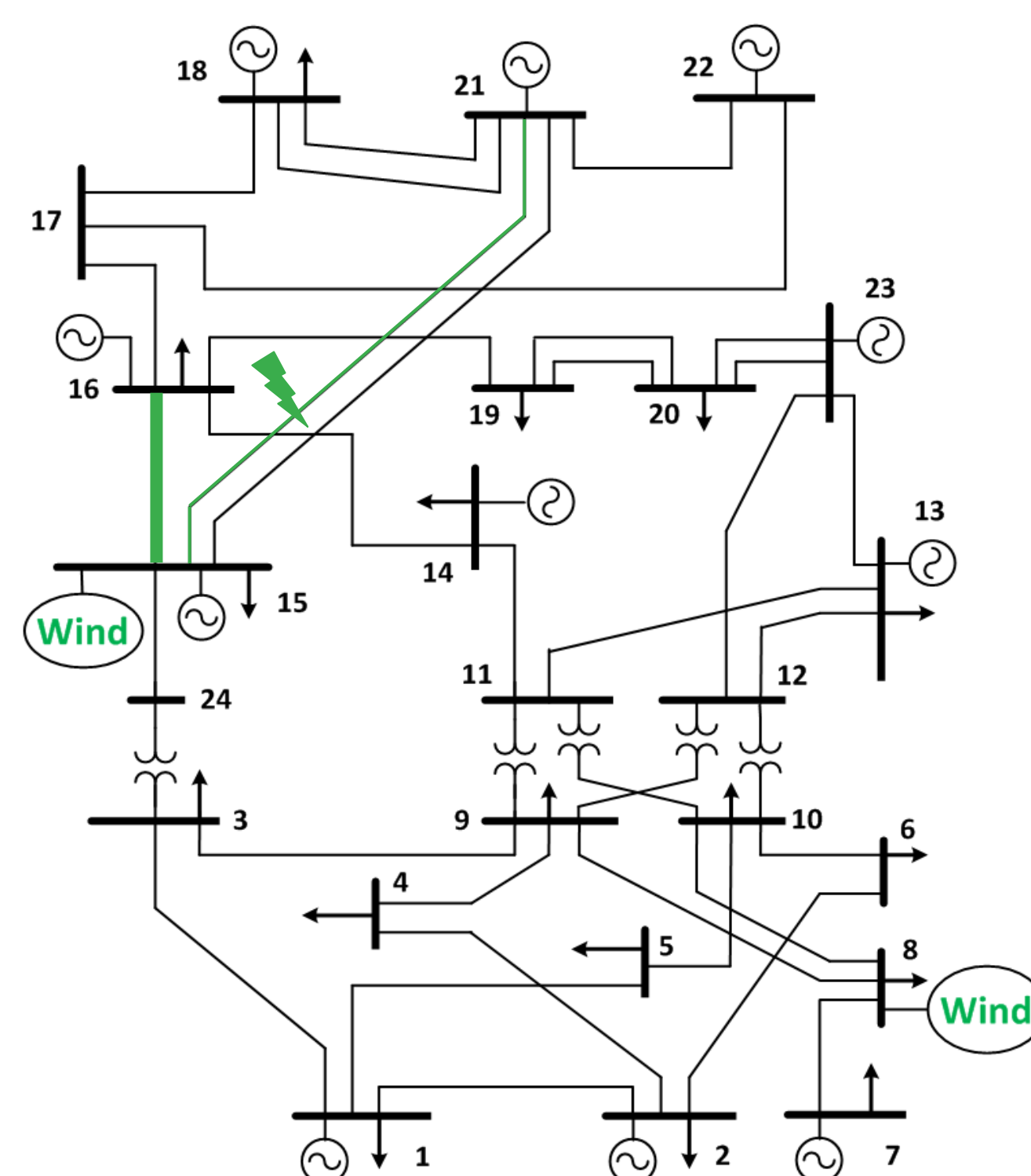
Active constraint: Power flow on line 15-16 after outage of line 15 – 21

Cumulative distribution function:



Normal distribution is a «good guess», but provides no probabilistic guarantees

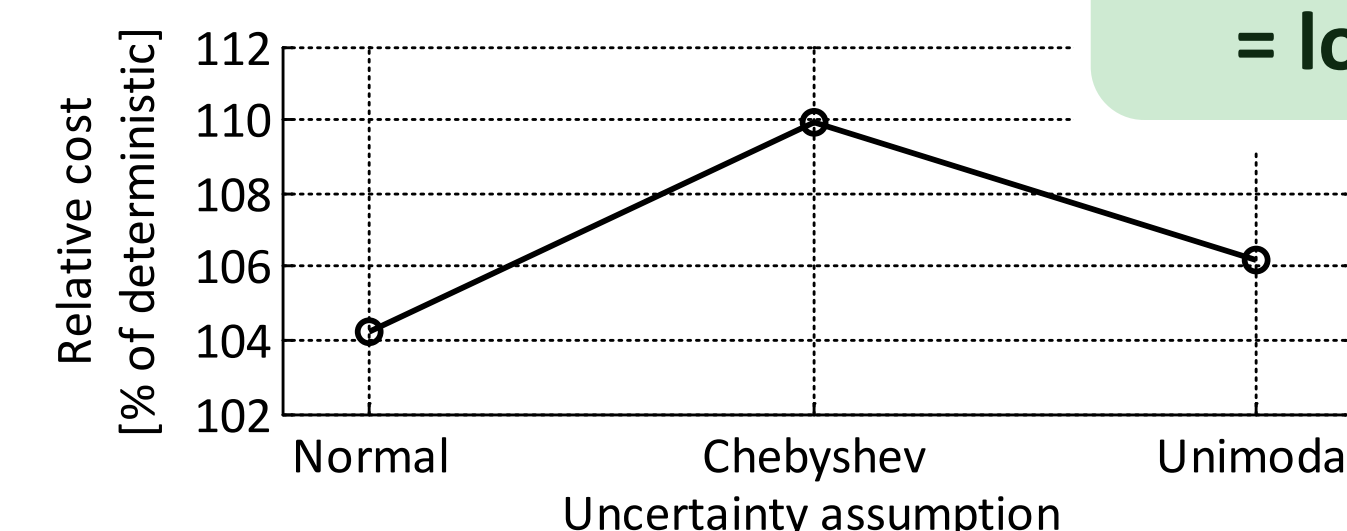
CASE STUDY RESULTS



Chebyshev provides probabilistic guarantees, but is very conservative

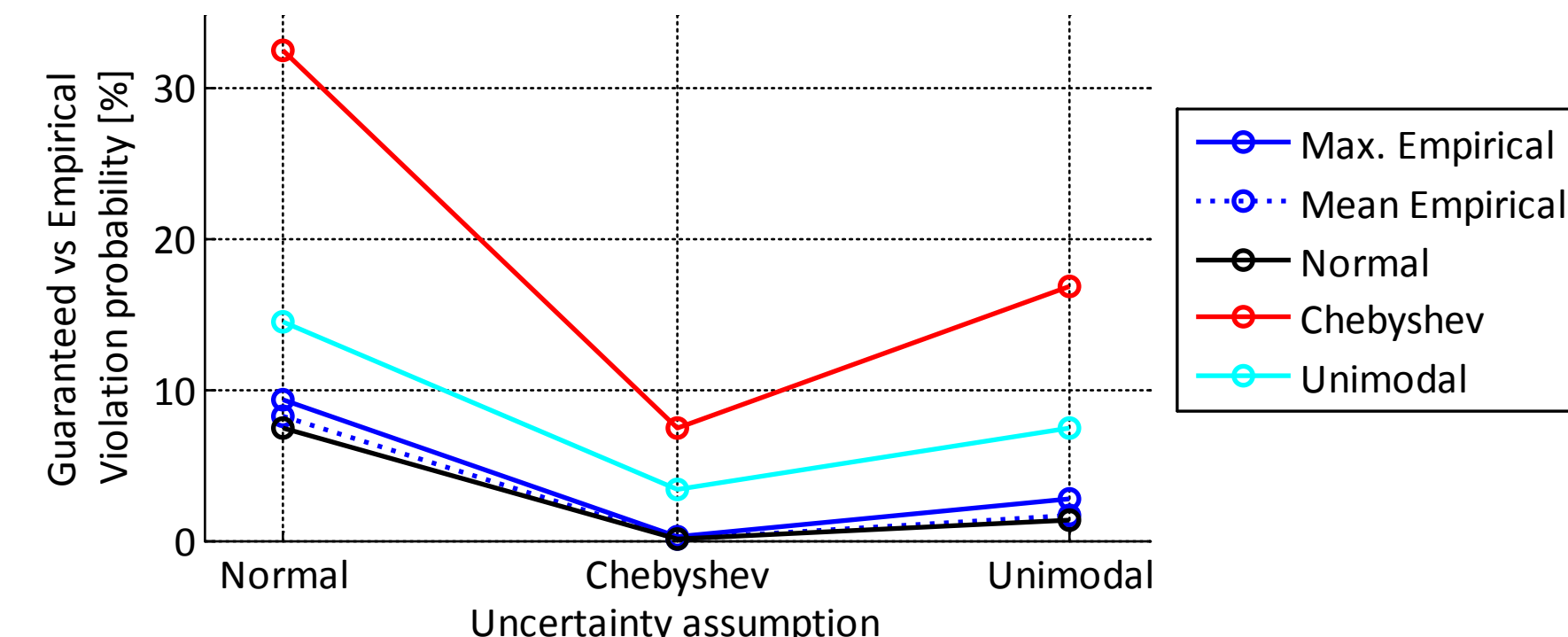
COST AND VIOLATIONS

Objective function cost



More information = lower cost

Empirical vs Guaranteed Violation probabilities



Unimodal provides probabilistic guarantees, and is less conservative

Abstract

We propose a new method to estimate the risk of large cascading blackouts triggered by multiple contingencies, using a search algorithm called “Random Chemistry”. Risk estimates converge at least two orders of magnitude faster than a conventional Monte-Carlo simulation for two test systems (e.g., Fig. 1). Using this method, we can quickly estimate how risk changes with load level (Fig. 2) and find the most critical components in a power grid (Fig. 3). We further propose a decentralized overload mitigation approach to stop a potential cascade (Fig. 4).

Estimating Cascading Failure Risk

A standard measure of risk due to a random disturbance:

$$R(x) = \sum_{c \in \Omega} \Pr(c) S(c, x)$$

Monte-Carlo $\rightarrow \hat{R}_{MC}(x) = \frac{1}{|\Omega_a|} \sum_{c \in \Omega_a} S(c, x)$

Random Chemistry $\rightarrow \hat{R}_{RC,k}(x) = \frac{m_k}{|\Omega_{RC,k}|} \sum_{d \in \Omega_{RC,k}} S(d, x) \left(\prod_{i \in d} p_i \right)$

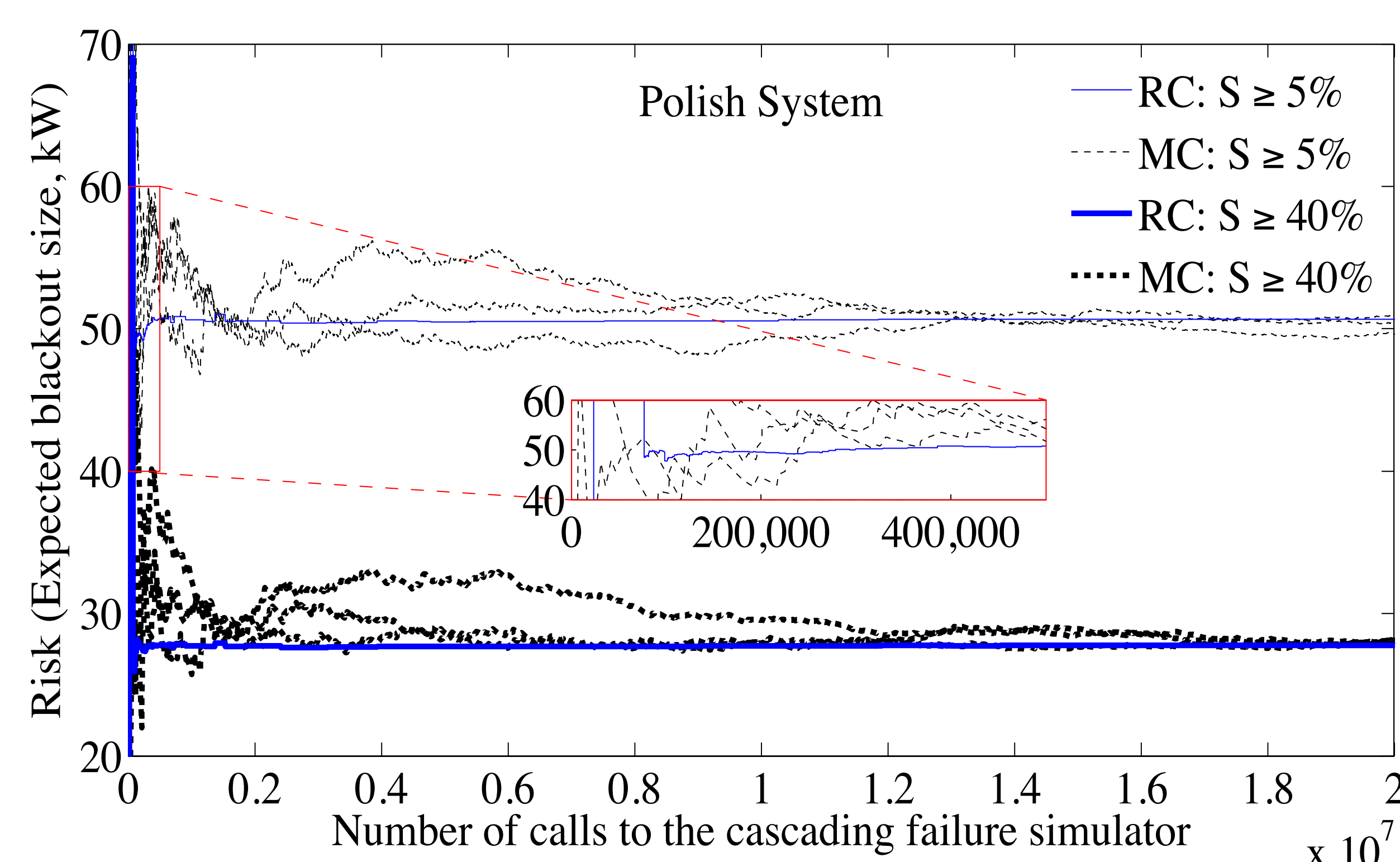


Figure 1. Cascading failure risk estimates using the Random Chemistry and Monte-Carlo methods in the Polish grid with 2896 branches.

Risk as a function of load

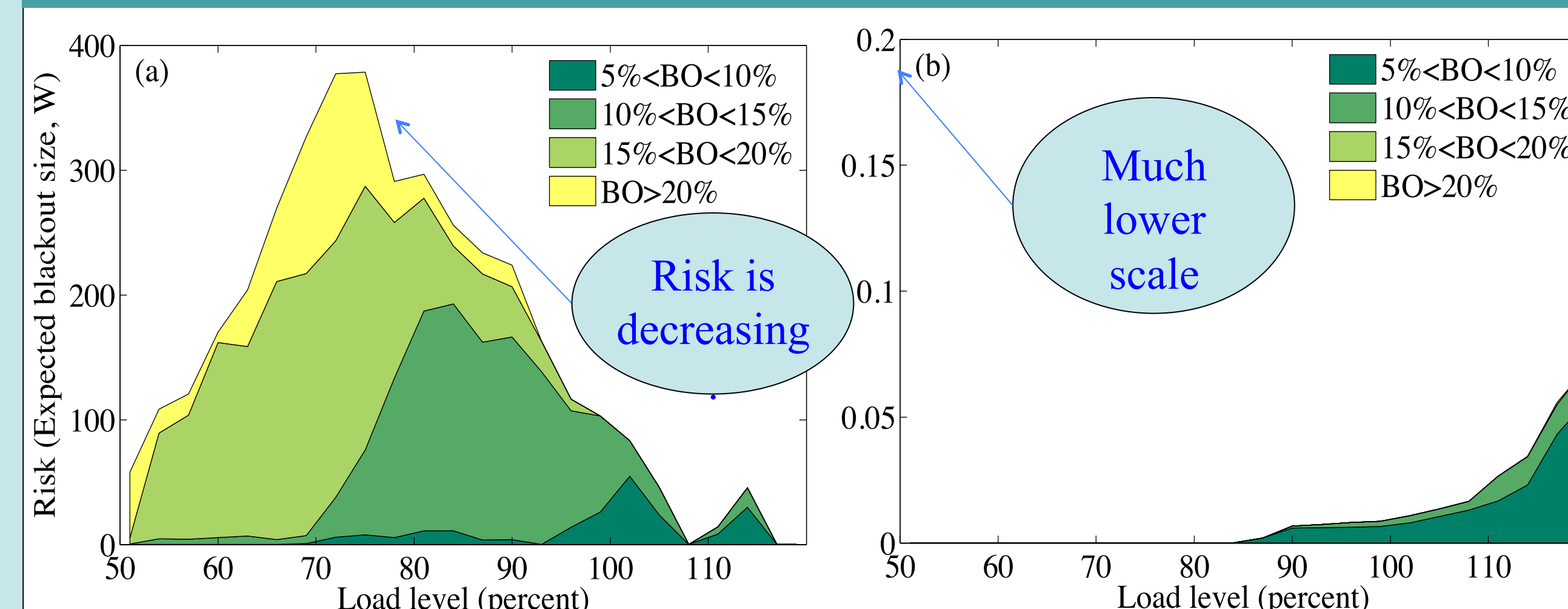


Figure 2. Cascading failure risk vs. load level for RTS-96: (a) SCDCOPF, and (b) Proportional dispatch. The proportional dispatch is more expensive, but has a much lower risk, which shows a trade-off between cost of dispatch and risk.

Sensitivity of Risk to individual branch outage probabilities

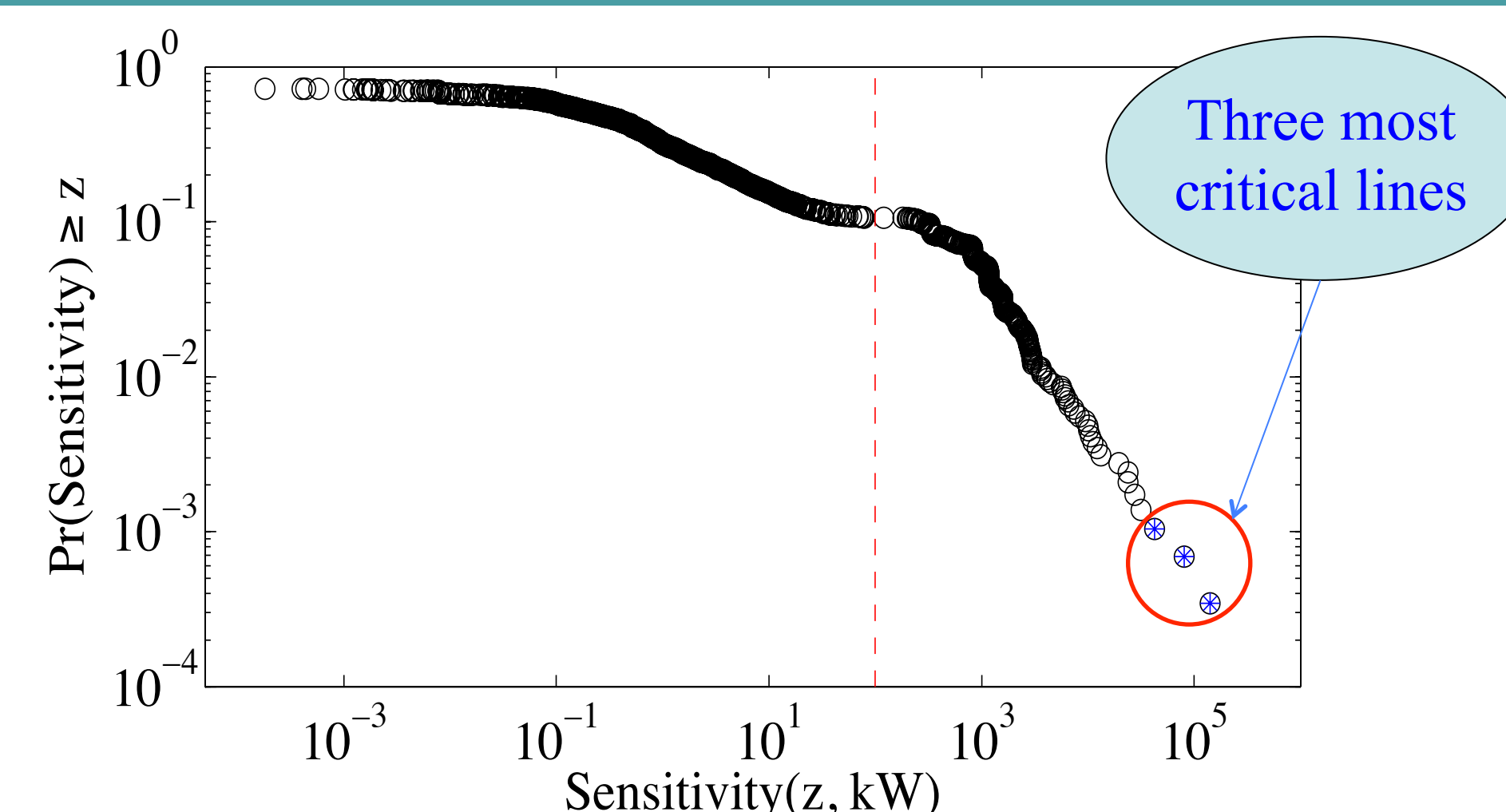


Figure 3. Complementary Cumulative Distribution Function of sensitivities (one circle per branch)

$$\frac{\partial \hat{R}_{RC,k}(x)}{\partial p_i} = \frac{m_k}{|\Omega_{RC,k}|} \sum_{d \in \Omega_{RC,k}} S(d, x) \left(\frac{\partial \Pr(d)}{\partial p_i} \right)$$

Disadvantages of Centralized Control

A central controller has certain flaws when it comes to implementation, which makes it impractical:

- It needs a huge communication infrastructure to collect and submit information to the whole network
- It is more vulnerable to failures. One failure in a part of the system can collapse the control scheme.
- There are multiple control regions in an actual large-scale power grid, with operators each being in charge of their own area.
- Variation in load/generation on a bus typically has localized effects and does not generally affect the whole system.

Decentralized Overload Mitigation Problem

$$\begin{aligned} & \text{Minimize} && -\mathbf{1}^T \Delta \mathbf{P}_{D,\Omega} + \Lambda^T \mathbf{f}_{\text{over},\Omega} \\ & \Delta \mathbf{P}_{D,\Omega}, \Delta \mathbf{P}_{G,\Omega} \\ & \text{subject to} && \Delta \mathbf{f} = \mathbf{X}_b^{-1} \mathbf{A}^T \Delta \boldsymbol{\theta} \\ & && -\mathbf{f}_{\text{max},\Omega} - \mathbf{f}_{\text{over},\Omega} \leq \mathbf{f}_{0,\Omega} + \Delta \mathbf{f}_{\Omega} \leq \mathbf{f}_{\text{max},\Omega} + \mathbf{f}_{\text{over},\Omega} \\ & && \mathbf{B} \Delta \boldsymbol{\theta} = \mathbf{A}_G \Delta \mathbf{P}_G - \mathbf{A}_D \Delta \mathbf{P}_D \\ & && -(\mathbf{P}_{G0,\Omega} - \mathbf{P}_{G,\text{min},\Omega}) \leq \Delta \mathbf{P}_{G,\Omega} \leq 0 \\ & && -\mathbf{P}_{D0,\Omega} \leq \Delta \mathbf{P}_{D,\Omega} \leq 0 \\ & && \Delta \mathbf{P}_{G,\Omega^c} = 0 \\ & && \Delta \mathbf{P}_{D,\Omega^c} = 0 \\ & && \mathbf{f}_{\text{over},\Omega} \geq 0 \end{aligned}$$

Ω : node/line local neighborhood, Ω^c : nodes outside Ω
 $\Delta \mathbf{P}_D / \Delta \mathbf{P}_G$: variation in load/generation
 \mathbf{f}_{over} : slack variable to define a soft constraint for overload
 \mathbf{B} : bus susceptance matrix

After each agent solves their own optimization problem with the optimization control variables to exist only in the local neighborhood, it implements the load/generation reduction only on its own when negotiation is off, or the whole local neighborhood when negotiation is on.

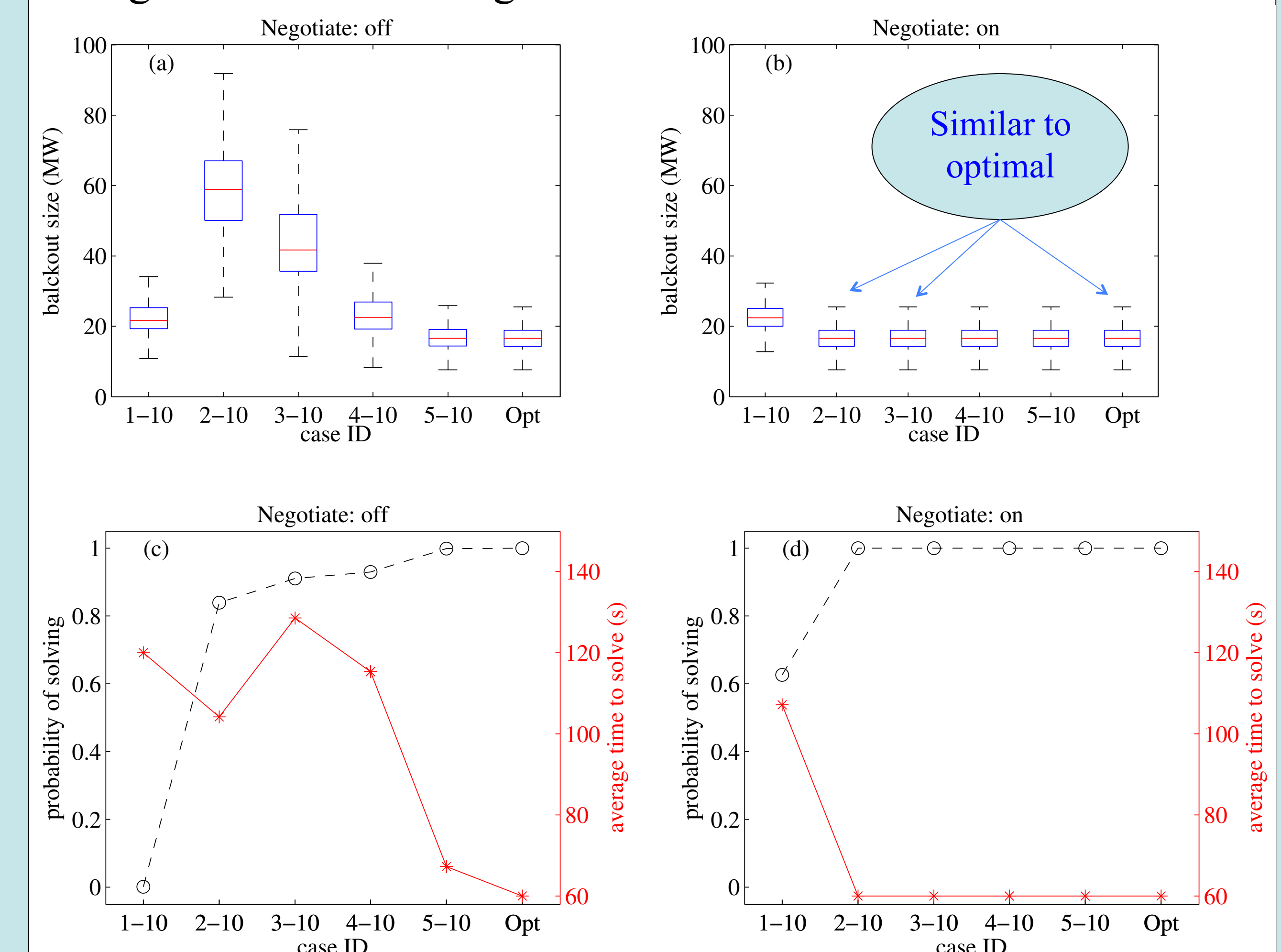


Figure 4. Statistical performance of the decentralized controller after applying all n-2 contingencies to a modified IEEE 30-bus case: The box plot indicates total blackout sizes, where the line shows the median value (a) without, and (b) with negotiation capability; bottom panels show empirical probability of eliminating overloads (dashed line and circle markers) and the average time (solid line and asterisk markers) that it takes to solve the problem (c) without, and (d) with negotiation. The case ID p-q represents the local neighborhood size p and extended neighborhood size q.

Constrained Mean Field Control for Large Populations of Plug-in Electric Vehicles

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Introduction

Vehicles obtaining some or all of their energy from the electricity grid, as Plug-in (hybrid) Electric Vehicles (PEVs), may achieve significant market penetration over the next few years. This raises the question of how to optimally fulfill the corresponding energy requirement, by regulating the collective charging profile of large populations of PEVs, while guaranteeing the interest and the privacy of the users.

Here we address this task using a mean field game theoretical approach [1,2]. We consider PEVs as heterogeneous agents, with different charging constraints (plug-in times and deadlines), that minimize their own charging cost and are weakly coupled via a common electricity price.

Problem Formulation

Consider a charging horizon of T time steps. Let $\mathbf{u}_n = [u_{n,1}, \dots, u_{n,T}]^\top$ be the vector of the energy required by vehicle $n \in \{1, \dots, N\}$, which must belong to the personalized constraint set

$$\mathcal{U}_n := \left\{ \mathbf{u}_n \in \mathbb{R}^T \mid \sum_t u_{n,t} = \gamma_n, \quad 0 \leq u_{n,t} \leq M_{n,t} \right\},$$

and $p(\mathbf{u}_t^{\text{avg}}) := a(u_t^{\text{avg}} + d_t)$, $a > 0$, be an affine price function that depends on the total energy demand at time t . Each agent minimizes its charging cost by solving

$$\mathbf{u}_n^* \left(\{\mathbf{u}_i\}_{i \neq n}^N \right) := \arg \min_{\mathbf{u}_n} \sum_t p(u_t^{\text{avg}}) u_{n,t} \quad (1)$$

s.t. $\mathbf{u}_n \in \mathcal{U}_n$

which leads to the aggregate behavior

$$\mathbf{u}^{\text{avg}} = \frac{1}{N} \sum_{n=1}^N \mathbf{u}_n.$$

As shown in Figure 1 (left) if uncontrolled the total energy demand may present undesirable peaks.

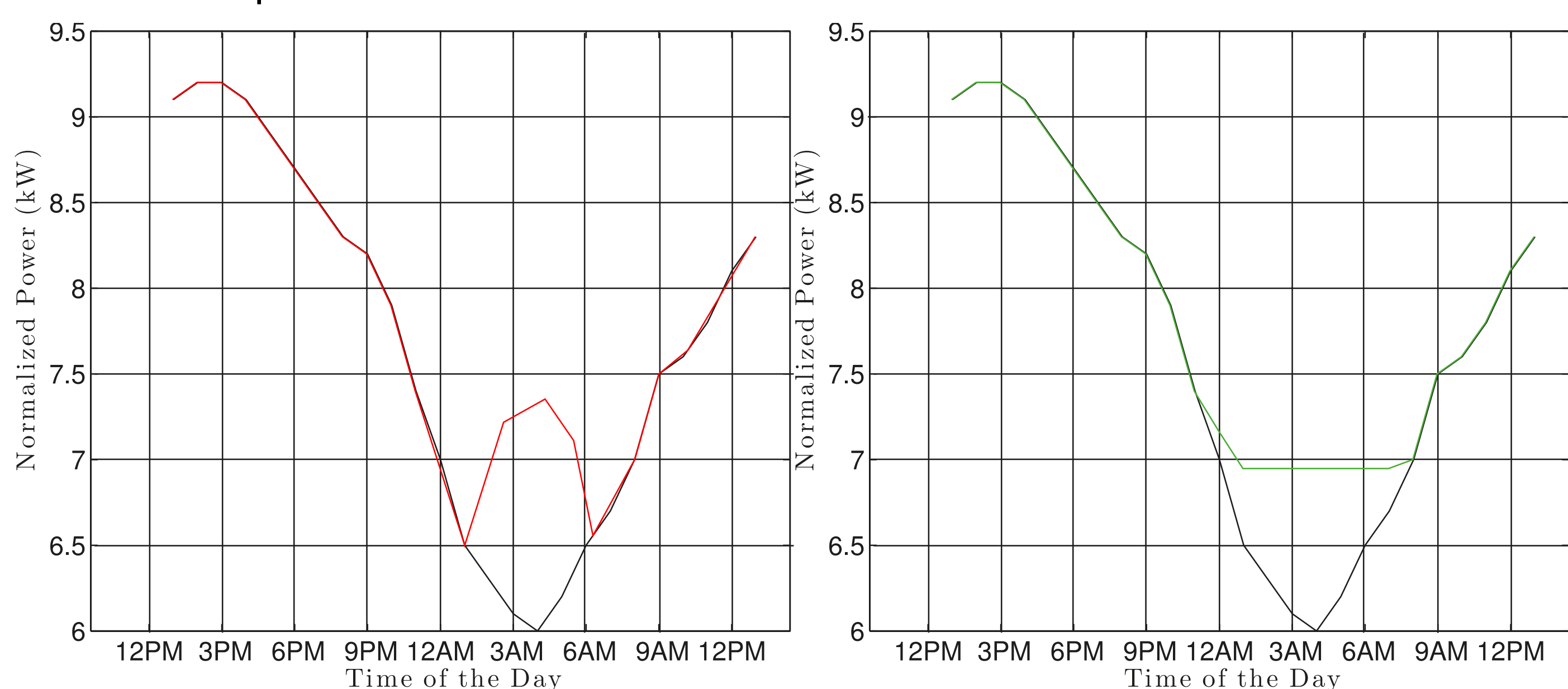


Figure 1 : Total energy demand divided by the number of vehicles N , according to different charging policies. The black line is the normalized base load demand d_t .

Nash Equilibrium

A set of strategies $\{\bar{\mathbf{u}}_n\}_{n=1}^N$ is stable if no agent has interest in deviating from its strategy given what the others are doing. Formally it is an ε -Nash equilibrium if

$$J(\bar{\mathbf{u}}_n | \{\bar{\mathbf{u}}_i\}_{i \neq n}^N) \leq J(\mathbf{u}_n | \{\bar{\mathbf{u}}_i\}_{i \neq n}^N) + \varepsilon \quad \forall \mathbf{u}_n \in \mathcal{U}_n.$$

It was proven in [3], that the Nash equilibrium of problem (1), *in the absence of upper bounds*, is valley-filling, see Figure 1 (right). Hence the Nash equilibrium is both **valley-filling** and **socially fair**.

To steer the population to such desirable equilibrium we consider a quadratic relaxation of the original problem using the modified cost

$$J_\delta(\mathbf{u}^{\text{avg}}) := \sum_t p(u_t^{\text{avg}}) u_{n,t} + \delta (u_{n,t} - u_t^{\text{avg}})^2$$

where the parameter $\delta > 0$ has to be as small as possible. Note that, in the limit of infinite population size, the average \mathbf{u}^{avg} can be thought of as an exogenous signal \mathbf{z} that must satisfy

$$\mathcal{A}(\mathbf{z}) := \frac{1}{N} \sum_{n=1}^N \mathbf{u}_n^*(\mathbf{z}) := \frac{1}{N} \sum_{n=1}^N \arg \min_{\mathbf{u}_n \in \mathcal{U}_n} J_\delta(\mathbf{z}) = \mathbf{z}.$$

$\bar{\mathbf{z}}$ fixed point of the aggregation mapping $\mathcal{A}(\cdot)$

⇓

$\{\mathbf{u}_n^*(\bar{\mathbf{z}})\}_{n=1}^N$ is an ε -Nash equilibrium, with $\varepsilon \sim \mathcal{O}(1/N)$

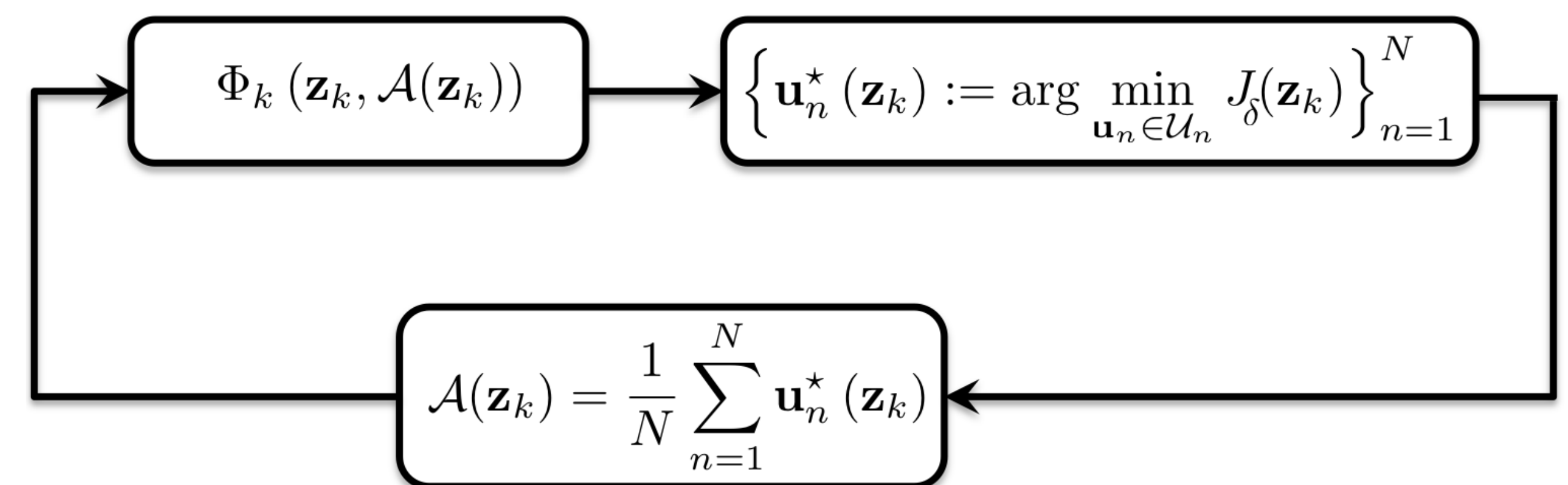
Acknowledgments

Research partially supported by the European Commission under project DYMASOS (FP7-ICT 611281), by the Swiss grant Nano-Tera.ch under project HeatReserves and by CTI under project SCCER-FEEB&D.

A Mean Field Control Algorithm

In order to find the fixed point of the aggregation mapping we consider an iterative scheme between

- a *central operator* that broadcasts at each iteration k the price signal $p(\mathbf{z}_k)$,
 $\mathbf{z}_k := \Phi_{k-1}(\mathbf{z}_{k-1}, \mathcal{A}(\mathbf{z}_{k-1}))$;
- the *agents* that respond by computing $\mathbf{u}_n^*(\mathbf{z}_k)$;
- an *aggregator* that computes $\mathcal{A}(\mathbf{z}_k)$ and send it back to the central operator.



The iteration-dependent feedback mapping $\Phi_k(\cdot, \cdot)$ should be selected such that the algorithm converges to a fixed point of the aggregation mapping. To this end, we consider two fixed point iteration mappings

Picard-Banach [3] : $\Phi^{\text{P-B}}(\mathbf{z}_k, \mathcal{A}(\mathbf{z}_k)) := \mathcal{A}(\mathbf{z}_k)$
Mann [4] : $\Phi^{\text{M}}(\mathbf{z}_k, \mathcal{A}(\mathbf{z}_k)) := (1 - \alpha_k)\mathbf{z}_k + \alpha_k \mathcal{A}(\mathbf{z}_k), \quad \alpha_k \propto 1/k$

The following convergence guarantees hold

	$\Phi^{\text{P-B}}$	Φ^{M}
$\delta > a/2$	✓	✓
$\delta > 0$		✓

Simulation

The use of the Mann iteration instead of the Picard-Banach allows one to find the fixed point for arbitrarily small values of δ , hence allowing to recover the Nash-equilibrium of the original Problem (1), [4]

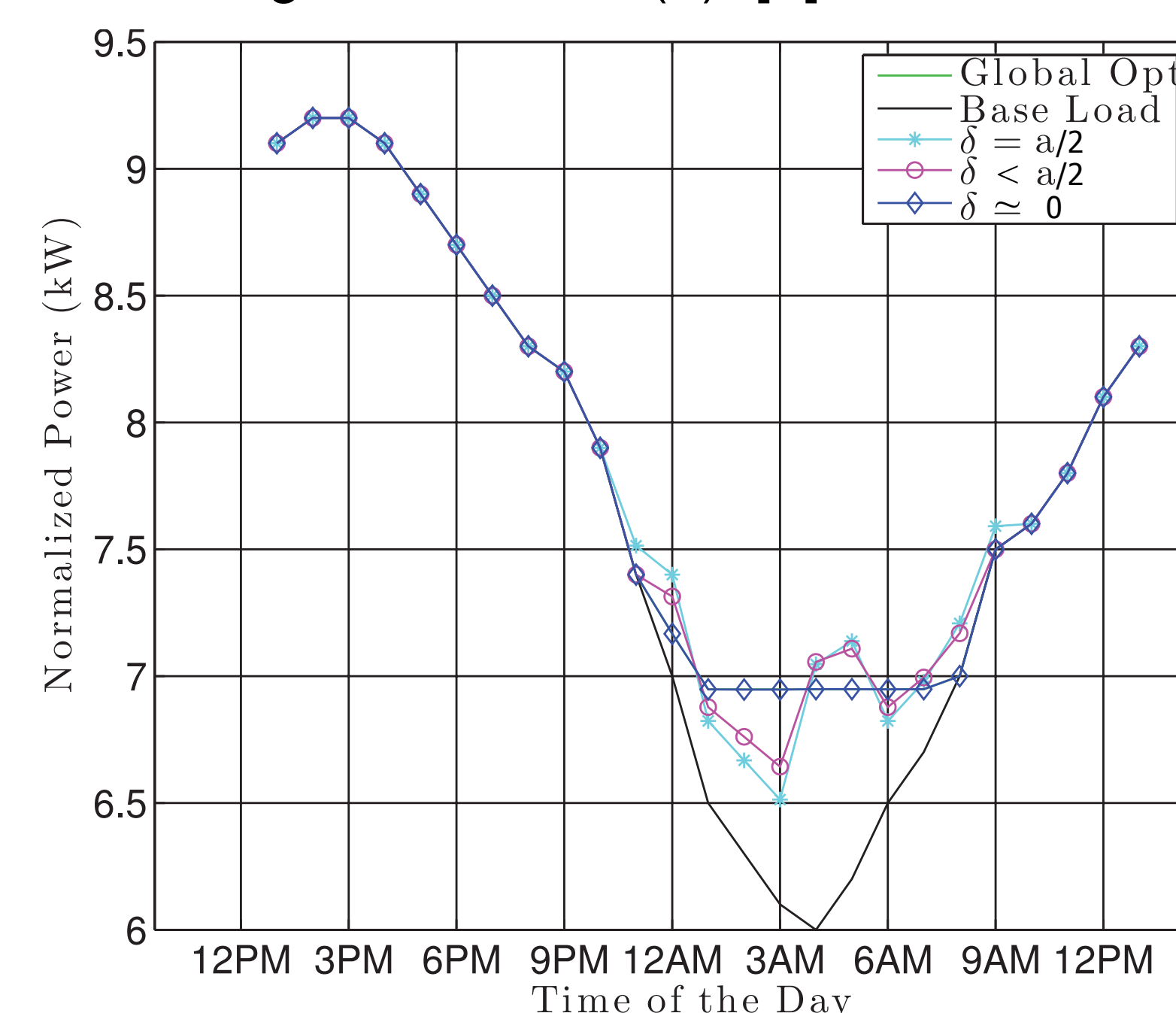


Figure 2 : Normalized total energy consumption relative to the Nash-equilibrium for different values of δ .

Generalization

The above results can be generalized to the broader class of quadratic, convex constrained, mean field games where each agent computes

$$\mathbf{x}_n^*(\mathbf{z}) := \arg \min_{\mathbf{x}} \mathbf{x}^\top Q \mathbf{x} + (\mathbf{x} - \mathbf{z})^\top \Delta (\mathbf{x} - \mathbf{z}) + 2(\mathbf{C}\mathbf{z} + \mathbf{c})^\top \mathbf{x}$$

s.t. $\mathbf{x} \in \mathcal{X}_n$

In [5], it is proven that, under different conditions on the matrices Q, Δ, C , different feedback mappings $\Phi(\mathbf{z}, \mathcal{A}(\mathbf{z}))$ can be used to steer the population to an ε -Nash equilibrium, with $\varepsilon \sim \mathcal{O}(1/N)$.

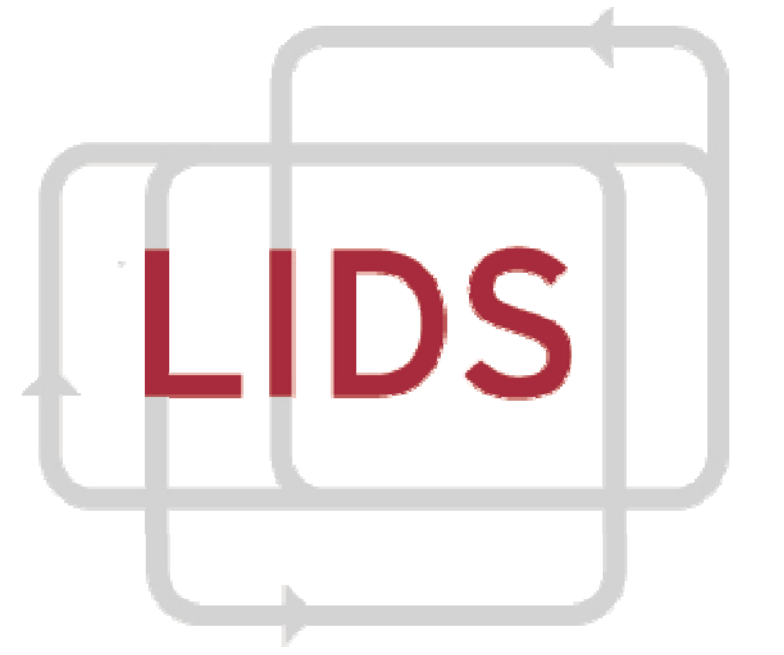
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- [3] Ma, Callaway, and Hiskens, "Decentralized charging control of large populations of plug-in electric vehicles", IEEE Trans. on Control Systems Technology, 2013.
- [4] Parise, Colombino, Grammatico, and Lygeros, "Mean field constrained charging policy for large populations of plug-in electric vehicles", IEEE CDC, 2014.
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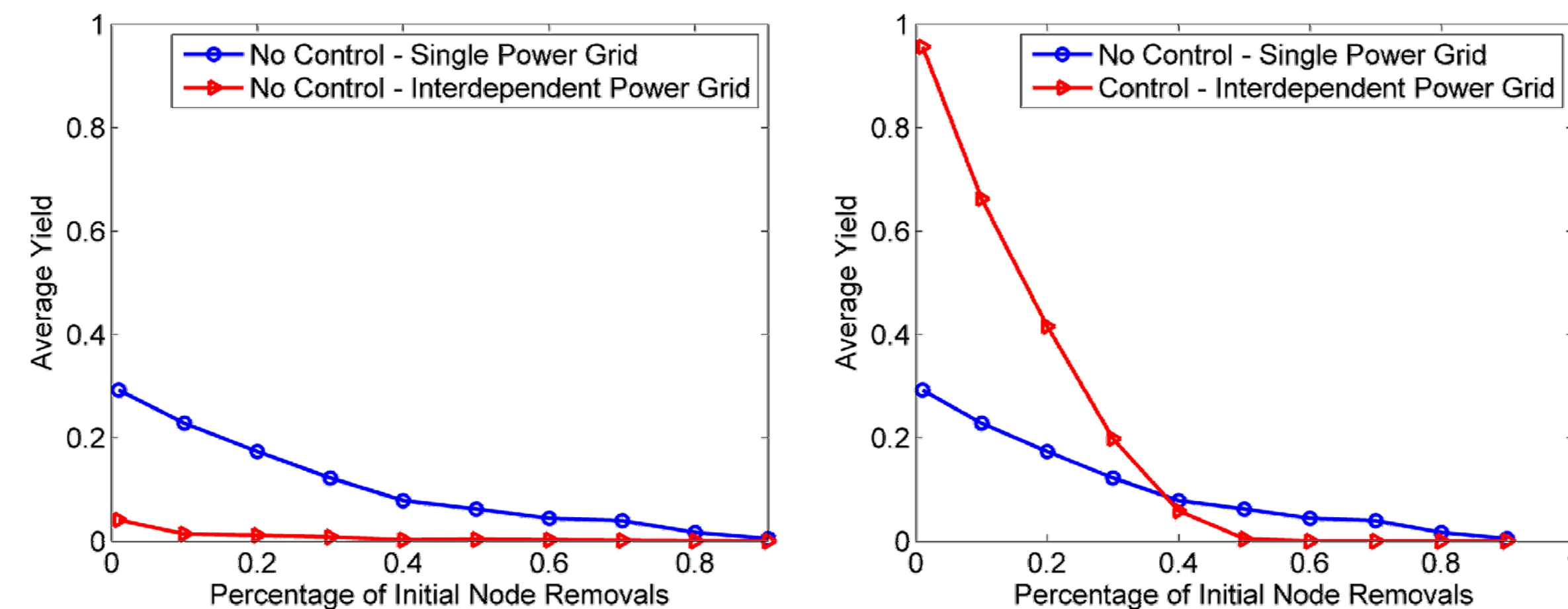
Investigating the Impact of Communication Loss on Power Grid Stability during a Large Disturbance

Marzieh Parandehgheibi, Konstantin Turitsyn and Eytan Modiano
(marp,turitsyn,modiano@mit.edu)



Introduction

- In order to avoid large cascading failures, a communication network is required for online monitoring & control
- Power grid and communication network make a strong interdependency
- Literature suggests that interdependency makes networks more vulnerable
- A proper analysis of interdependent networks should account for the availability of control schemes applied by the communication networks



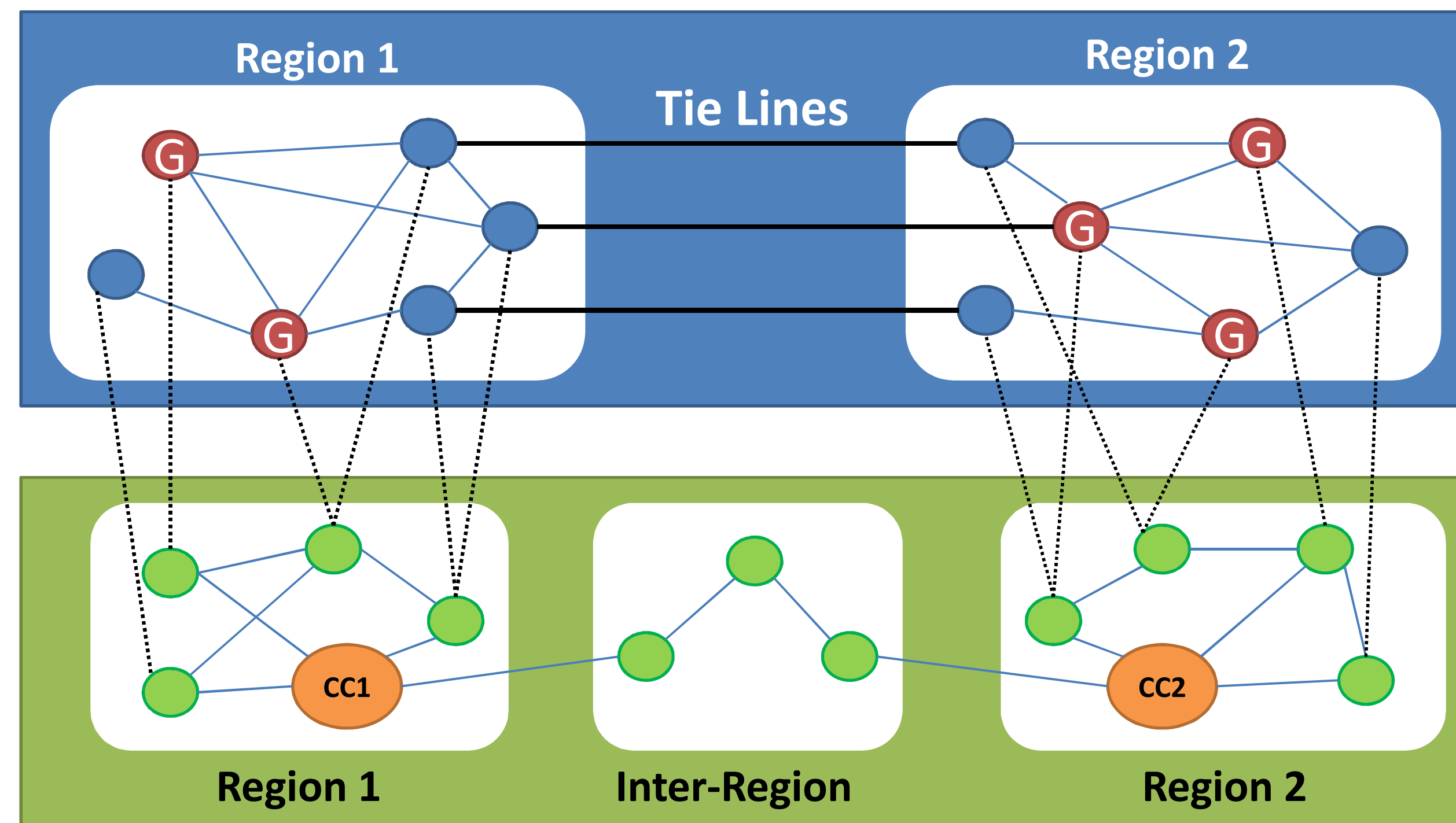
Interdependency increases the robustness of power grid

Question:

A point-wise failure model seems too simplistic.
How does the loss of communication network impact the power grid?

Ideal Model of Communication Network Responsible for Wide-Area Control

Power Grid



Communication Network

Types of Communication Failures:

- Intra-Region
- Inter-Region

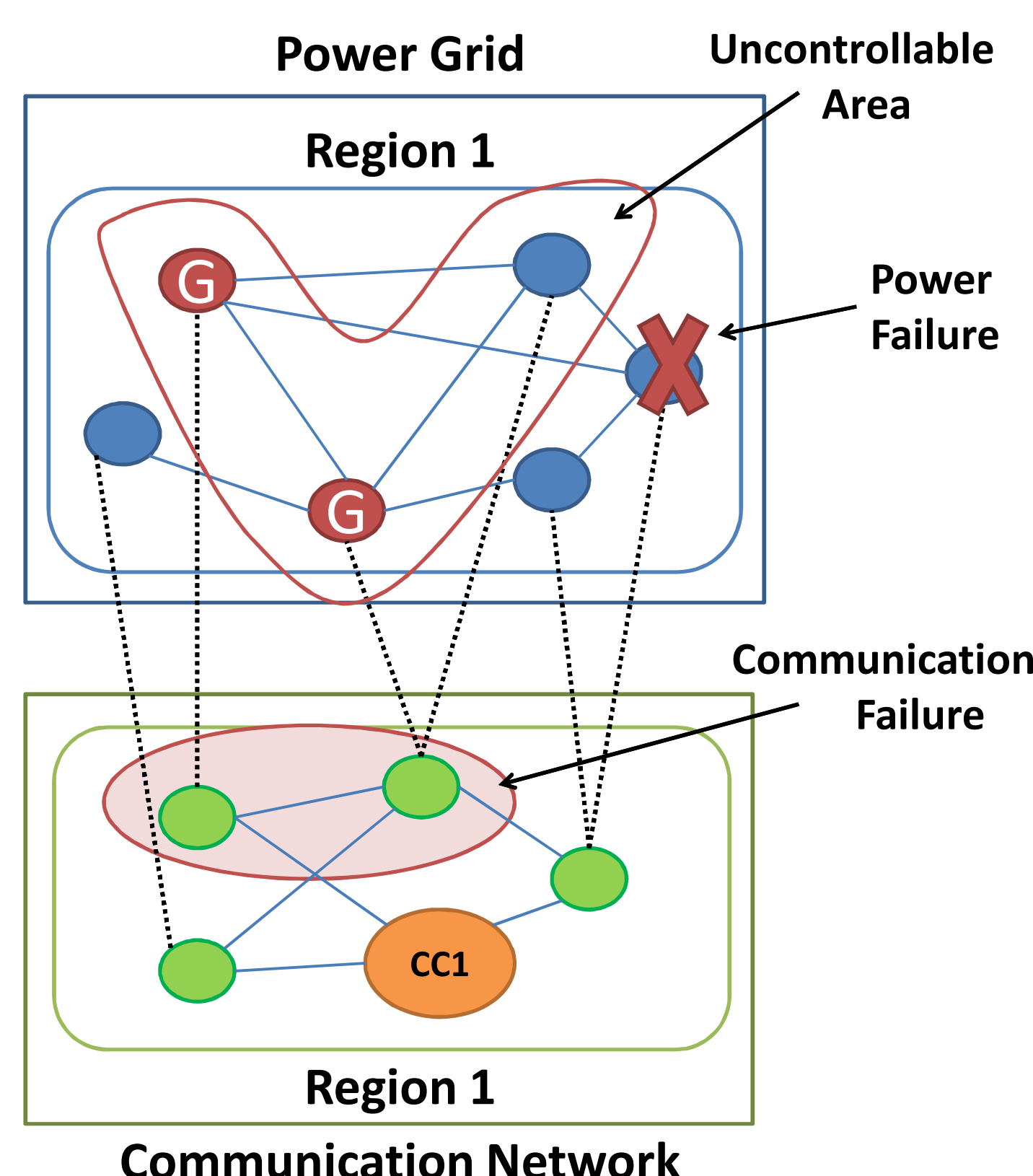
Intra-Region Failures:

- 1) Uncontrollable area and power failures are **disjoint**:

- Complete Information about the last state of Grid
- Partial Control

- 2) Uncontrollable area and power failures **overlap**:

- Incomplete Information about the state of Grid
- Partial Control



Role of Communication Network

Information collected by Communication Network

$V_k(t)$	Magnitude of voltage at node k
$\theta_k(t)$	Phase of voltage at node k
$\omega_k(t)$	Frequency of Power at node k
$f_{kj}(t)$	Flow in power line (k,j)

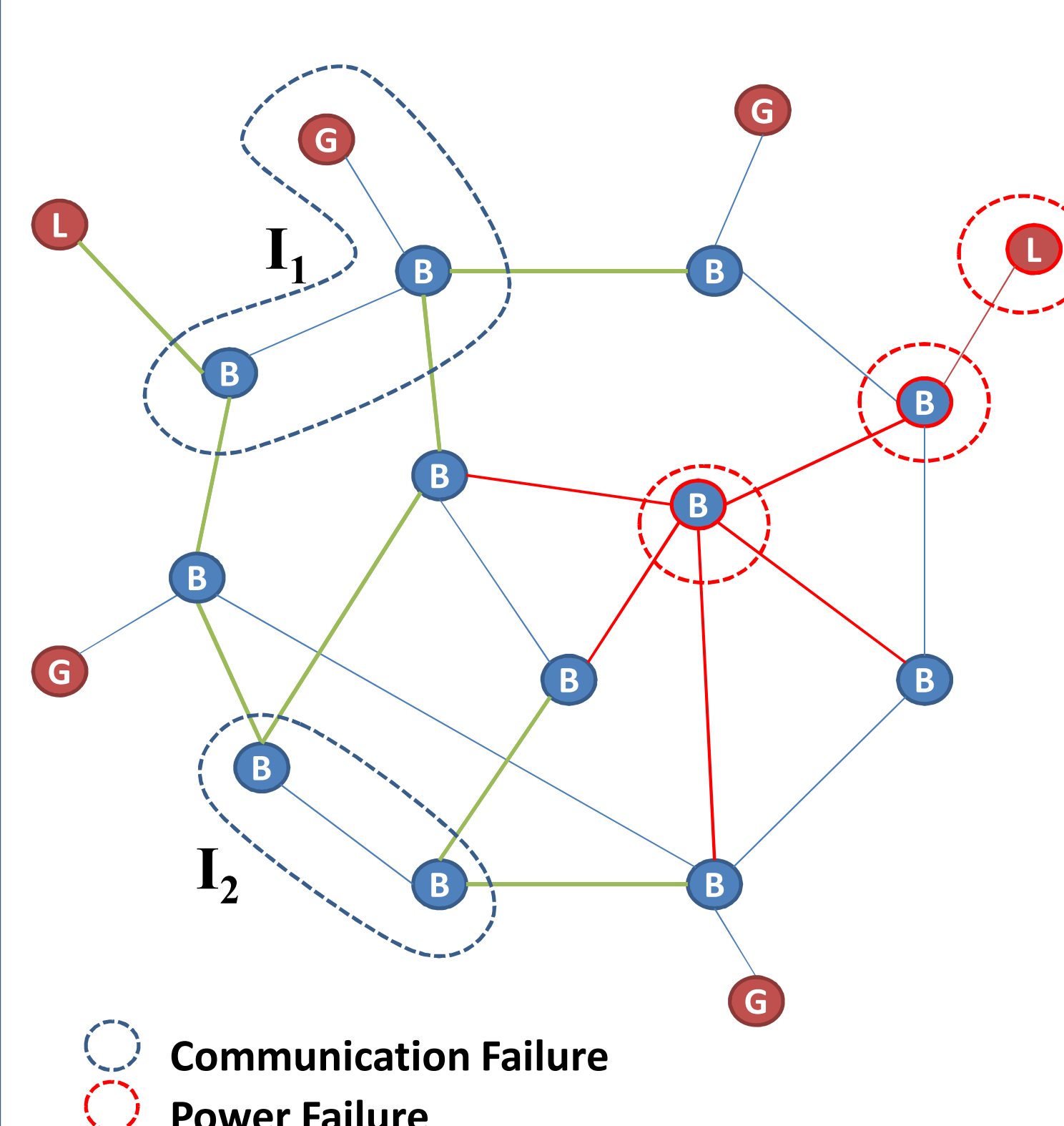
Control Actions

Centralized Control Requires Communication	Decentralized control-protection Performs locally- No Need to Communication
Ramping down generators	5% droop control at generators
Intelligent load shedding	Over-frequency generator tripping (protection)
Intelligent line tripping	Under-frequency load shedding (protection)
	Overloaded line tripping (protection)

Full Control Model

$$\begin{aligned} \min \quad & \sum_{i \in V_G} PL_i \\ & \sum_{j \in E} f_{ij} - \sum_{j \in E} f_{ji} = PG_i - \alpha_i(\omega_i - \omega_s) \quad \forall i \in V_G \\ & \sum_{j \in E} f_{ij} - \sum_{j \in E} f_{ji} = PL_i \quad \forall i \in V_L \\ & \sum_{j \in E} f_{ij} - \sum_{j \in E} f_{ji} = 0 \quad \forall i \in V_B \\ & -M(1-z_{ij}) \leq X_{ij} f_{ij} - \Delta \theta_{ij} \leq M(1-z_{ij}) \quad \forall (i,j) \in E \\ & -z_{ij} f_{ij}^{\max} \leq f_{ij} \leq z_{ij} f_{ij}^{\max} \quad \forall (i,j) \in E \\ & -M(1-z_{ij}) \leq \omega_i - \omega_j \leq M(1-z_{ij}) \quad \forall (i,j) \in E \\ & \omega_i^{\min} \leq \omega_i \leq \omega_i^{\max} \quad \forall i \in V_G \\ & PG_i^{\min} \leq PG_i \leq PG_i^{\max} \quad \forall i \in V_G \\ & PL_i^{\min} \leq PL_i \leq PL_i^{\max} \quad \forall i \in V_L \\ & z_{ij} \in \{0,1\} \quad \forall (i,j) \in E \end{aligned}$$

Partial Control Model



Controllable Areas: Full control

- Uncontrollable areas:**
1. Switch the Generators and Loads to a predefined strategy for CommLossMode;
 2. Allow Trip border lines

Objective: Stabilize Grid

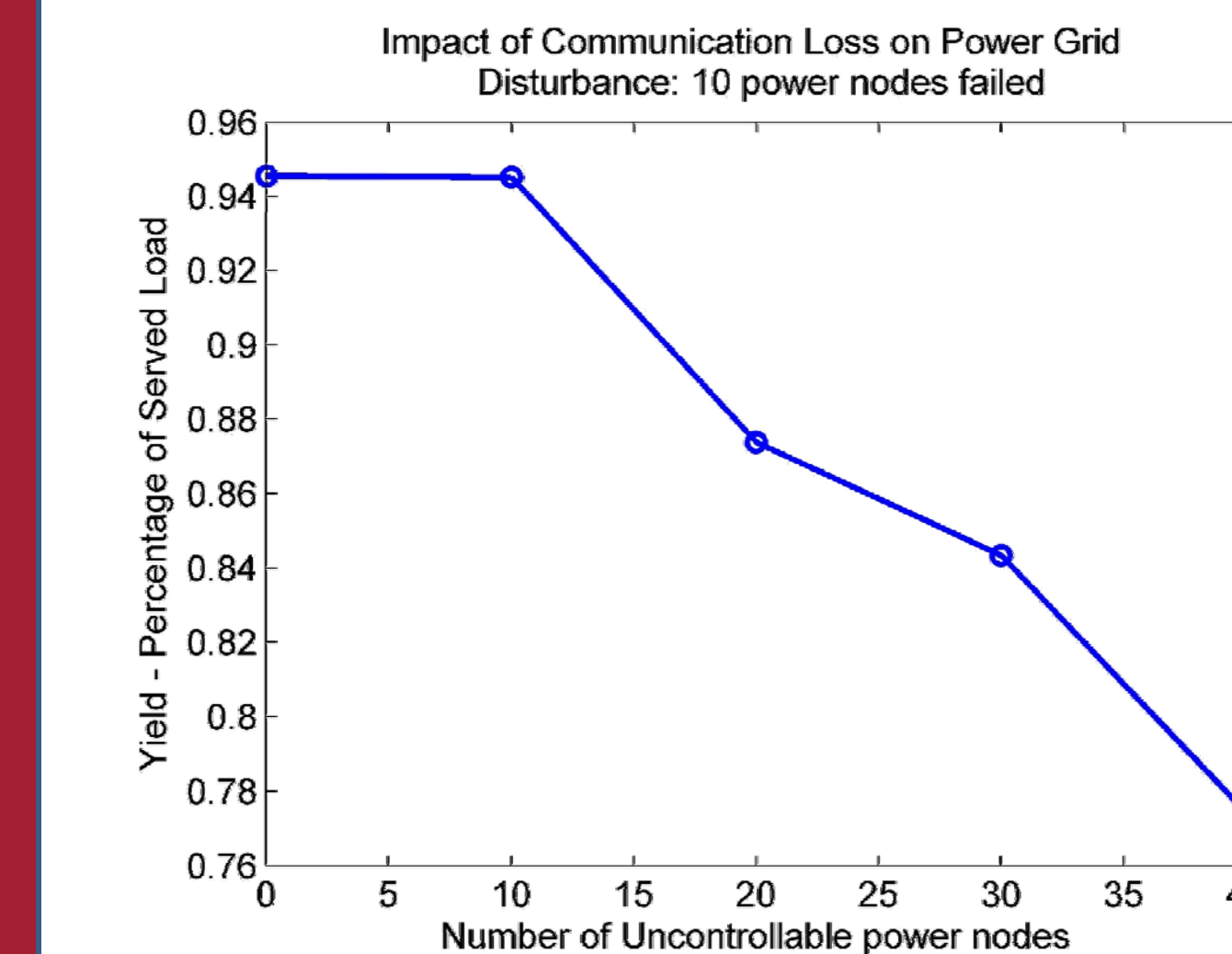
- a) Minimize Load Shedding while keeping the nodes in the uncontrollable area at a predefined strategy
- b) If keeping an uncontrollable area connected to the rest of grid is not feasible or costs a lot: Trip all border lines

Simulation Results

- Metric:** Yield (Percentage of served load)
- Pre-defined Strategy:** The state of power nodes after disconnection from the communication network
- 1) P_{init} : Keep the generators and loads at their last state
- 2) P_{zero} : Trip the generators and shed the loads

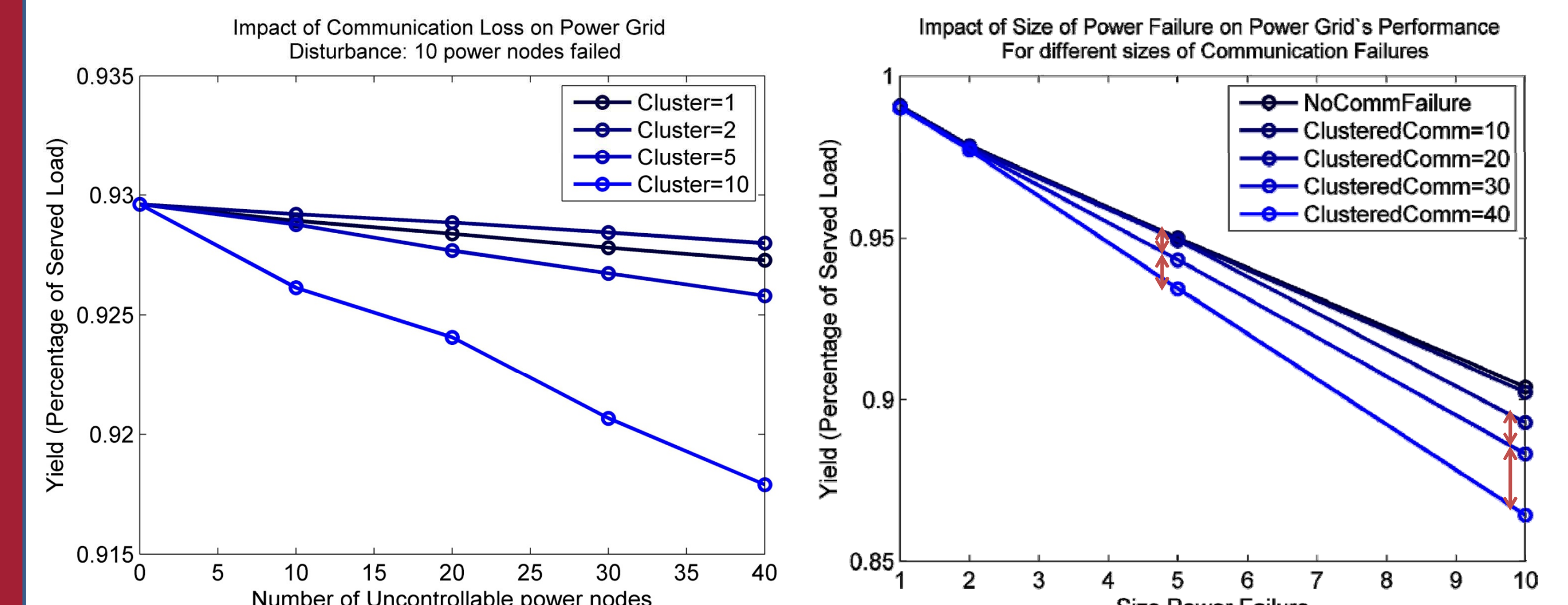
Observations:

- Communication loss makes network more vulnerable (smaller yield)



- Impact is a function of several parameters such as:

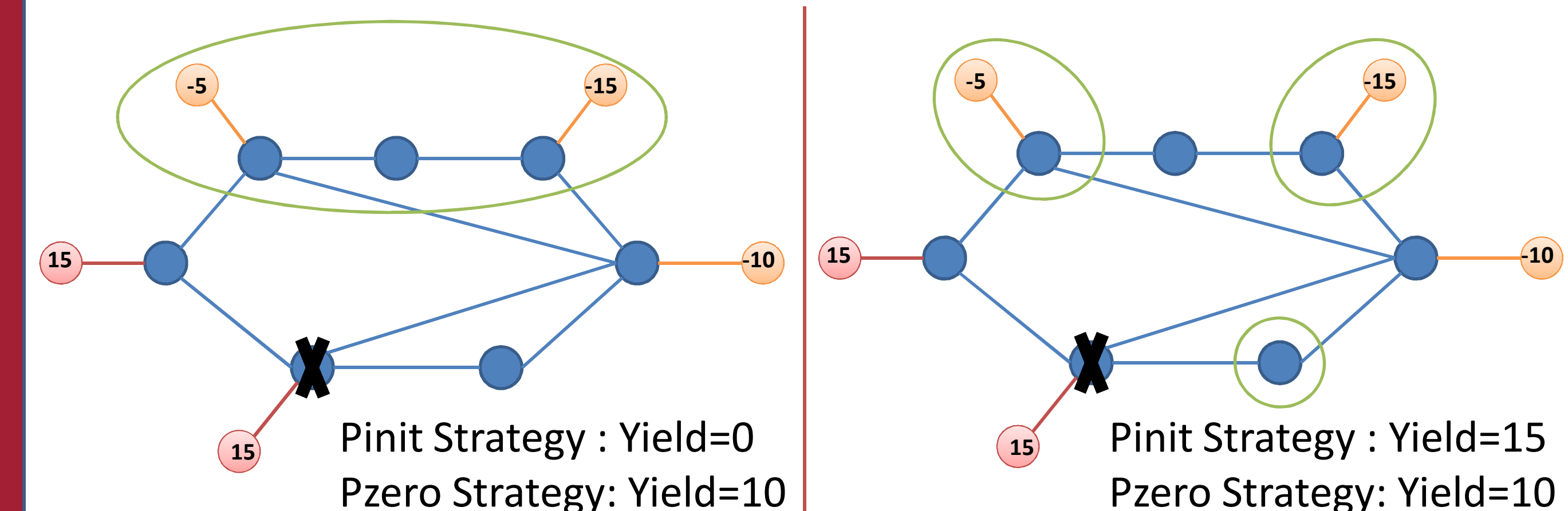
- 1) size of uncontrollable area: yield decreases monotonically
- 2) size of uncontrollable clusters (topology of uncontrollable area)
- 3) Size of Power Failure: yield decreases monotonically



- Nodes both inside and outside the uncontrollable area could be affected

- P_{init} is not always better than P_{zero}

- 1) For the same size of uncontrollable area, chance of $P_{zero} > P_{init}$ is higher in clustered areas
- 2) For the same size of clusters, chance of $P_{zero} > P_{init}$ is higher for smaller sizes of uncontrollable areas



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- Acknowledgement:** This work has been funded by DTRA grant HDTRA1-13-1-0021

Short Term Solar Forecasting Using Sky Imagery and Its Applications in Control and Optimization for a Smart Grid

Andu Nguyen (andunguyen@ucsd.edu) and Jan Kleissl (jkleissl@ucsd.edu) at UC San Diego's SRAF Lab

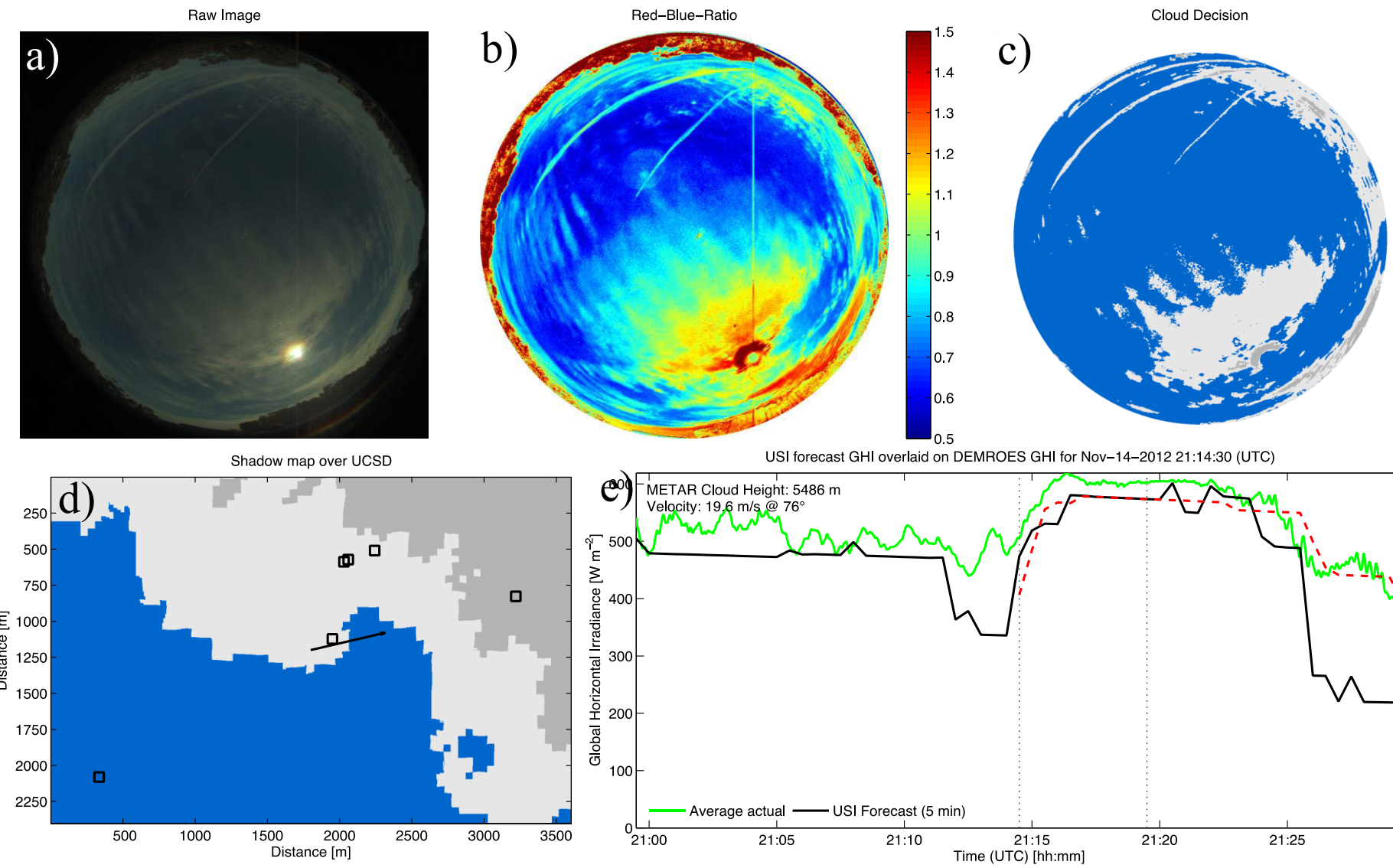
Short-term Solar Forecasting

Goal: Forecast solar generation in short time scale (0-30 minutes) with high temporal resolution to build smart controls for storage systems (charge/ discharge), power inverters, voltage regulators, smart switching devices, etc. This helps to save generation and maintenance cost while keeping power quality high.

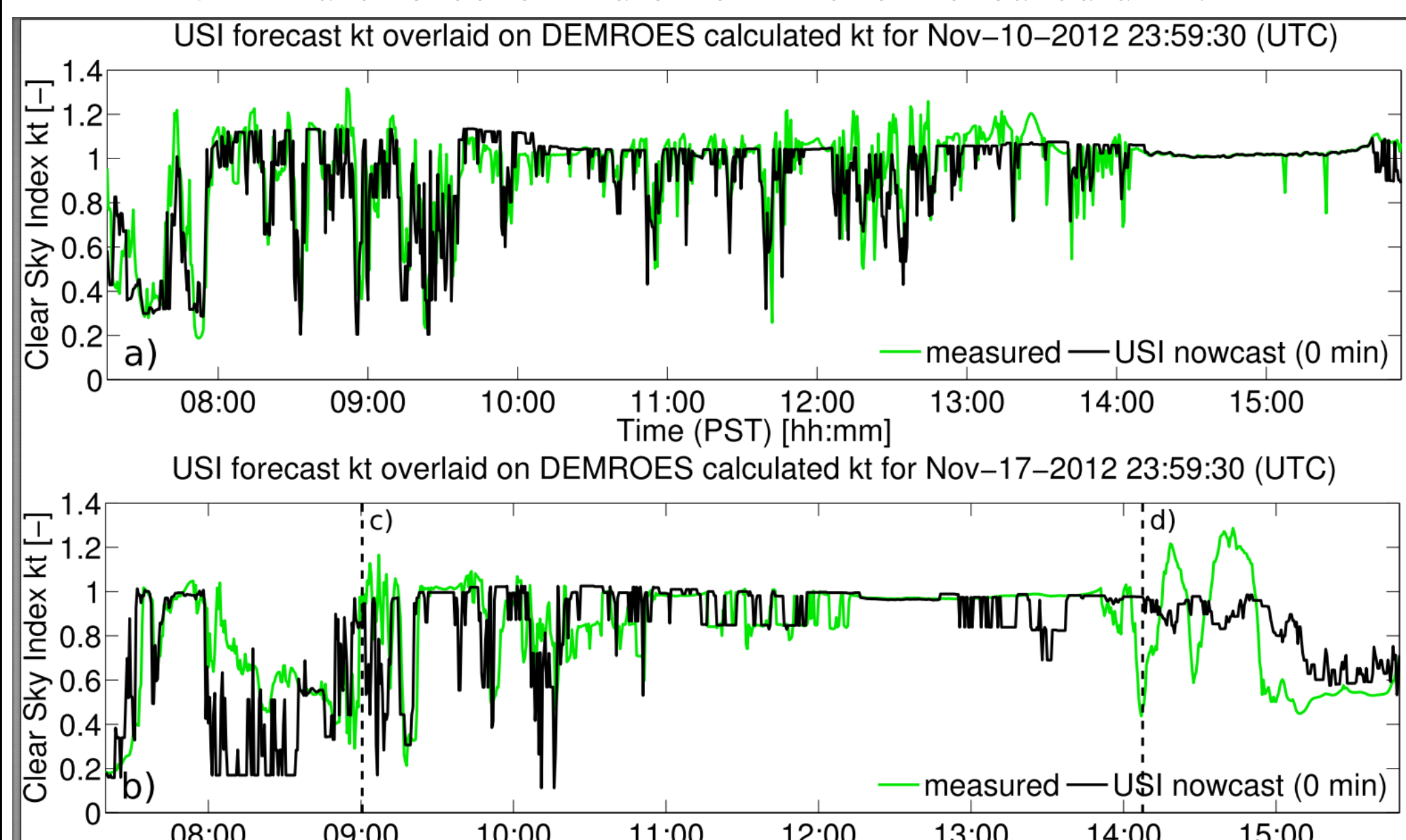


Algorithm: The fundamental idea is to detect cloud and predict its location in the future to determine whether and when it will cover the PV panels. The forecasting process includes several steps:

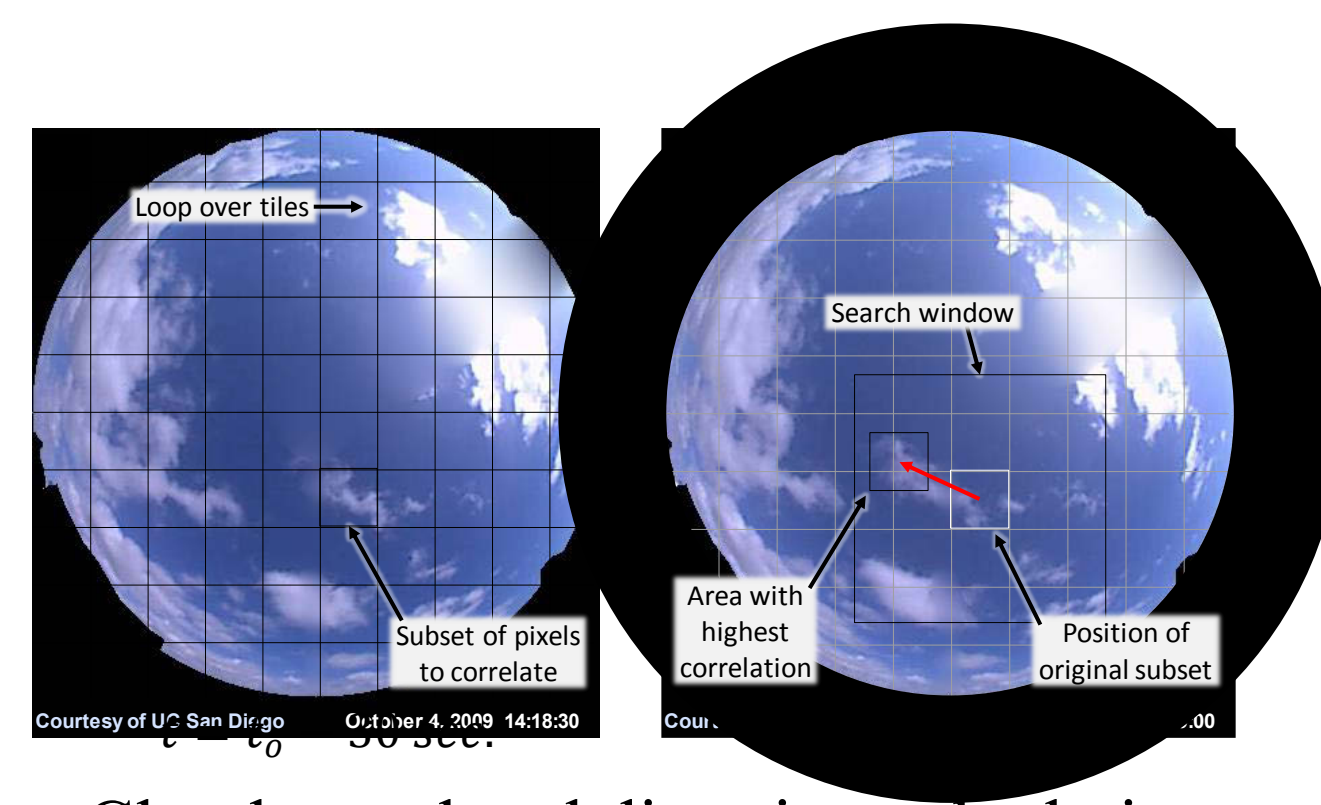
1. Cloud Detection: Using image processing to distinguish cloud from clear sky by RBR value.
2. Cloud projection into an earth coordinate system.
3. Cloud speed and direction calculation: Using image segment correlation.
4. Modeling cloud motion forward in time using the cloud detection and the motion vectors.
5. Projection of cloud shadows on the ground for irradiance forecasting of solar panels.



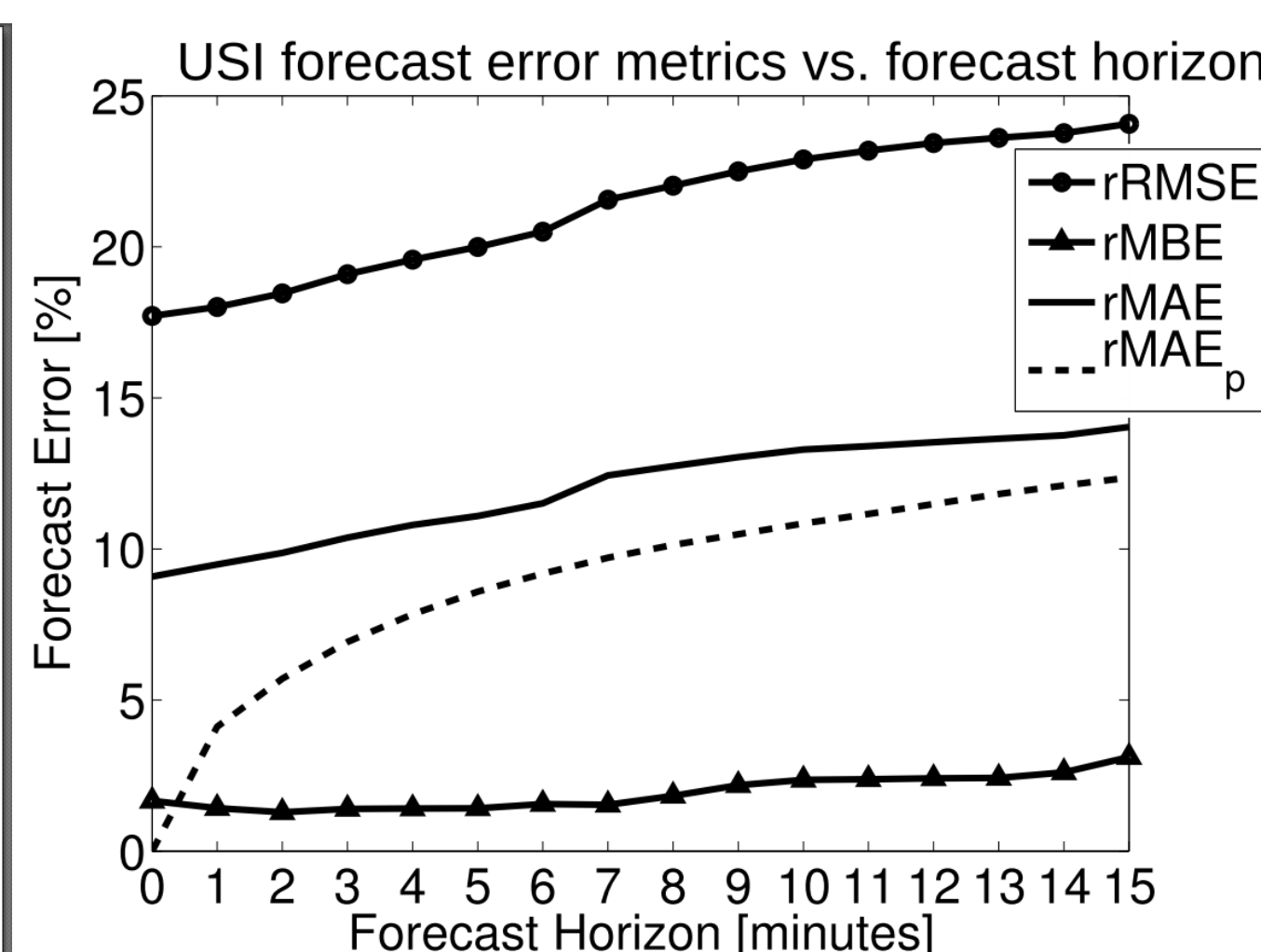
Sample of a forecast process done at UCSD. Green line is 5-minute forecast and black line is measured data.



USI forecast and measured *kt* averaged across 6 pyranometers at UCSD for Nov 10 and Nov 17 with cumulus clouds.



Cloud speed and direction calculation using image segment correlation

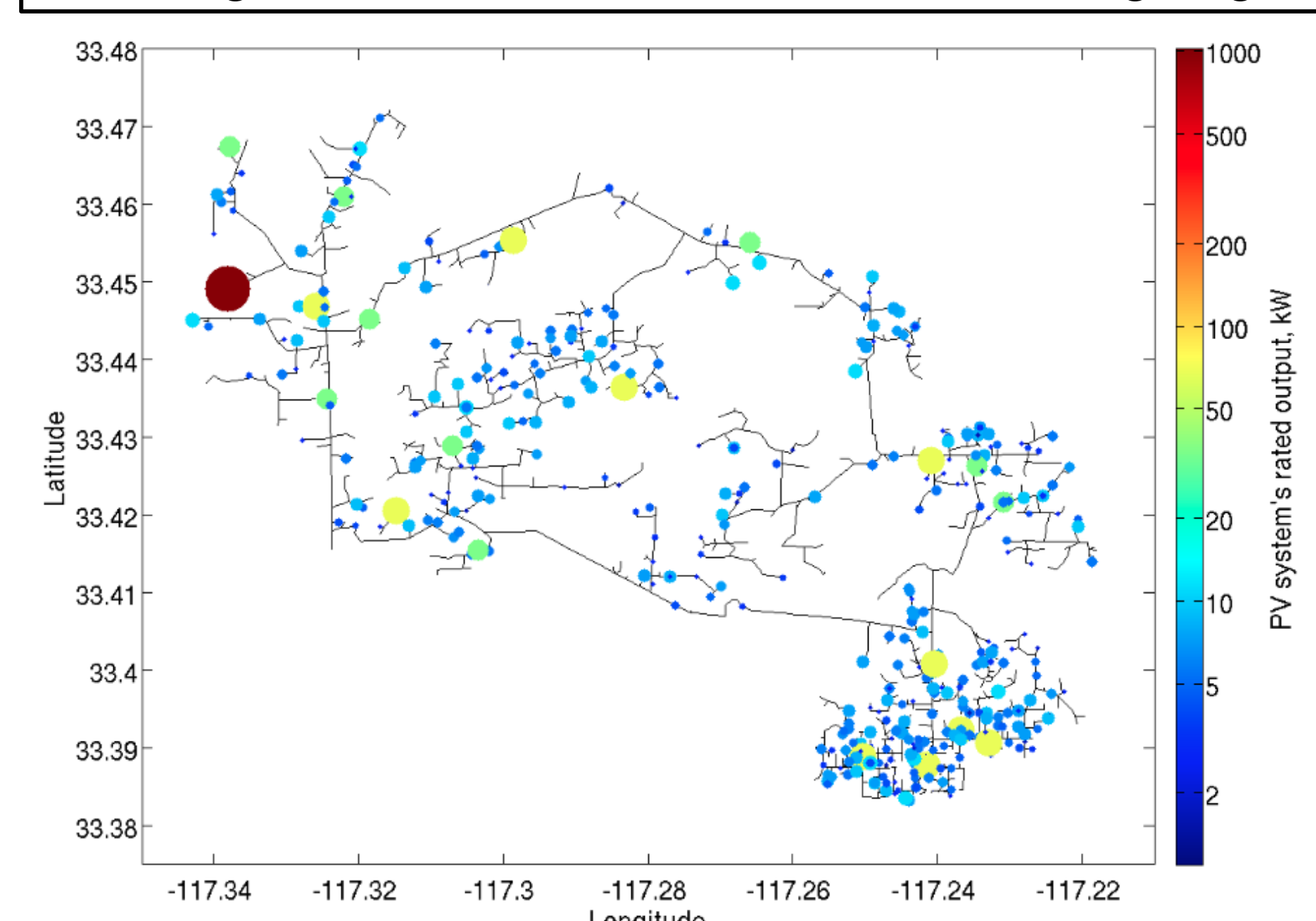


USI forecast's error metrics for all 31 days in Nov 2012. rMAE is 10% in average and increases as forecast horizon raises.

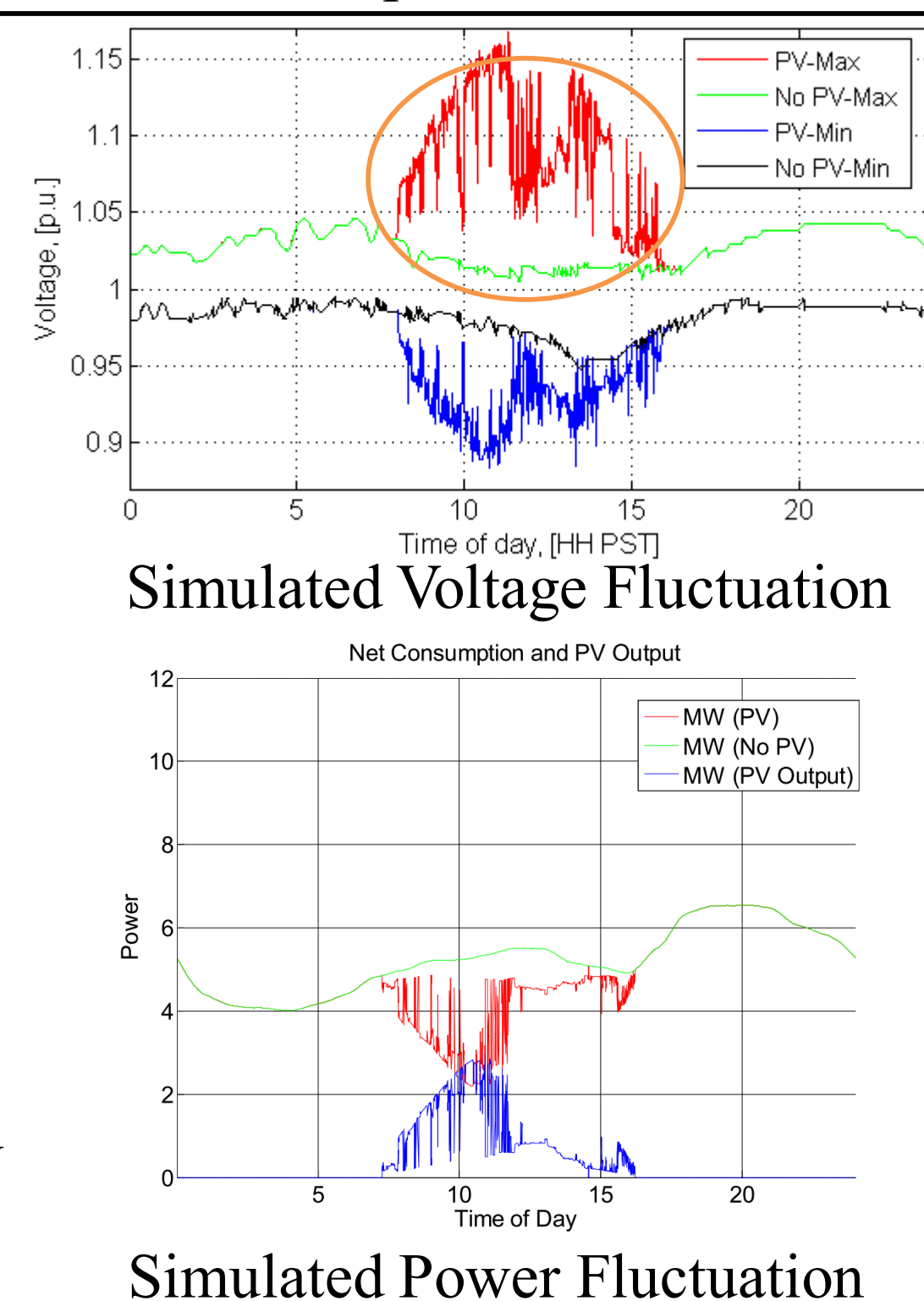
Issues with High PV Penetration

High PV penetration leads to various problems observed in both distribution and transmission systems:

- High frequency -> Impact frequency control and generators' synchronization -> power outage.
- Over-voltages -> damage electronic devices (light bulbs, computers, monitors, etc.)
- Voltage fluctuations -> shorten lifetime of voltage regulators, transformers, protection devices, etc.)



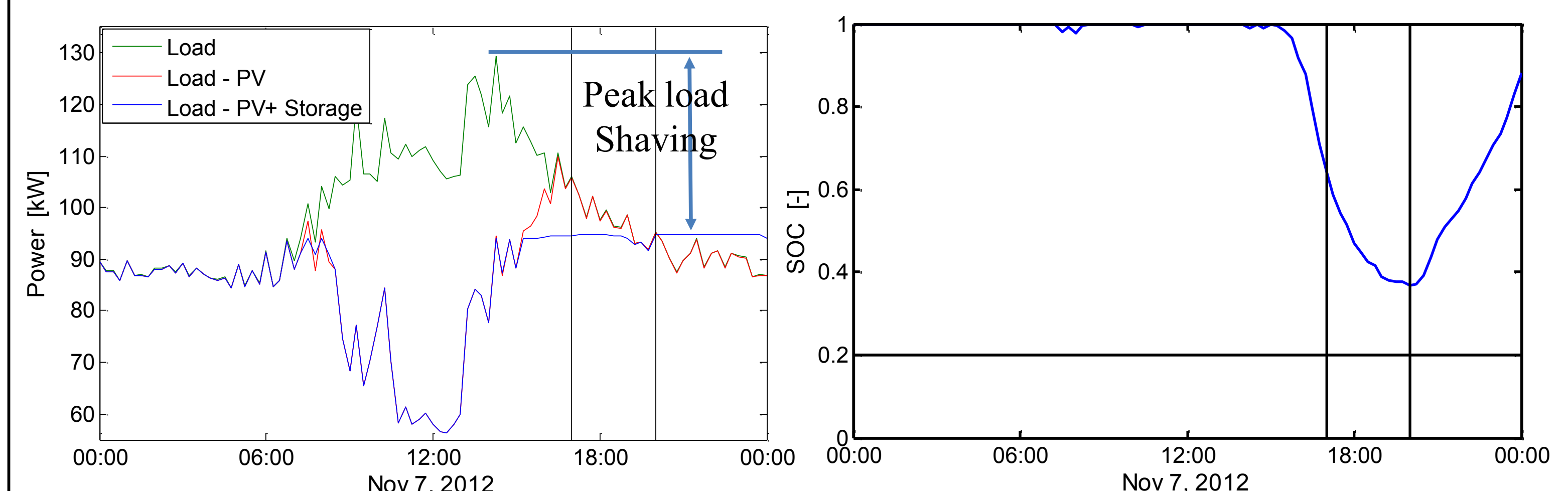
Real 12MW (1733 loads) SDGE distribution feeder with 2.3 MW PV. Simulated case with 5MW installed PV (42%) is shown.



Simulated Power Fluctuation

Peak load shaving control with Short-term Solar Forecast for Storage System

Control with Sky Imager Solar Forecast was developed for a 31kW PV tied to a 31 kWh Li-ion at John Hopkins parking structure at UCSD, CA. The solar forecasts was used to optimize the charge/discharge cycling for peak load shaving and battery life longevity. The strategy for peak load shaving is "Time-of-use Energy Cost Management Plus Demand Charge Management."



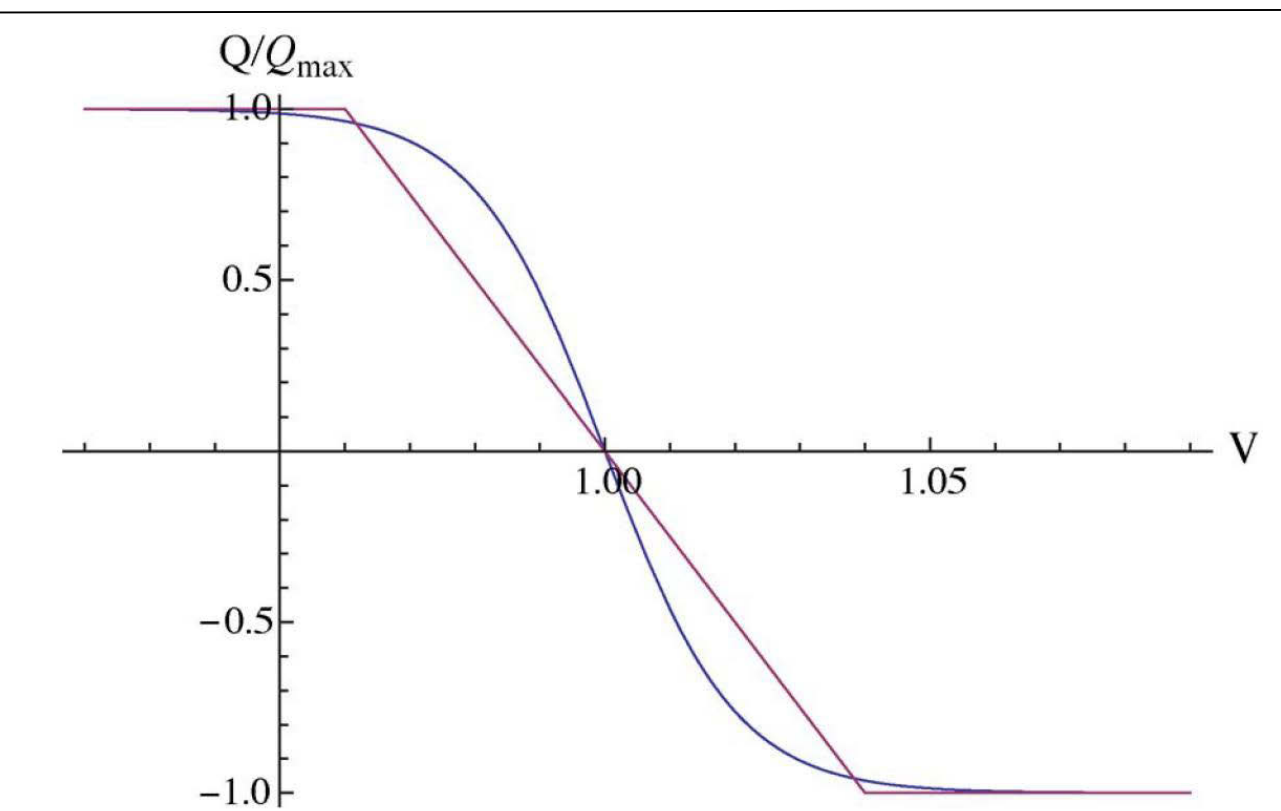
Control operation for Storage System at John Hopkins Building on Nov 7, 2012

	Optimization with PV Power Output and Load Forecast	Off-Peak/On-Peak without PV Power Output and Load Forecast
Annual energy bill cost reduction [\$]	33,200	30,500
Number of cycles at 80% DoD [cyc/yr]	212	365
Battery Lifetime [yrs]	14.2	8.2
Fixed cost simple payback time [yrs]	5.7	6.2
Total profit at end of battery lifetime (annual energy bill savings x battery lifetime - fixed costs) [\$]	281,000	60,000

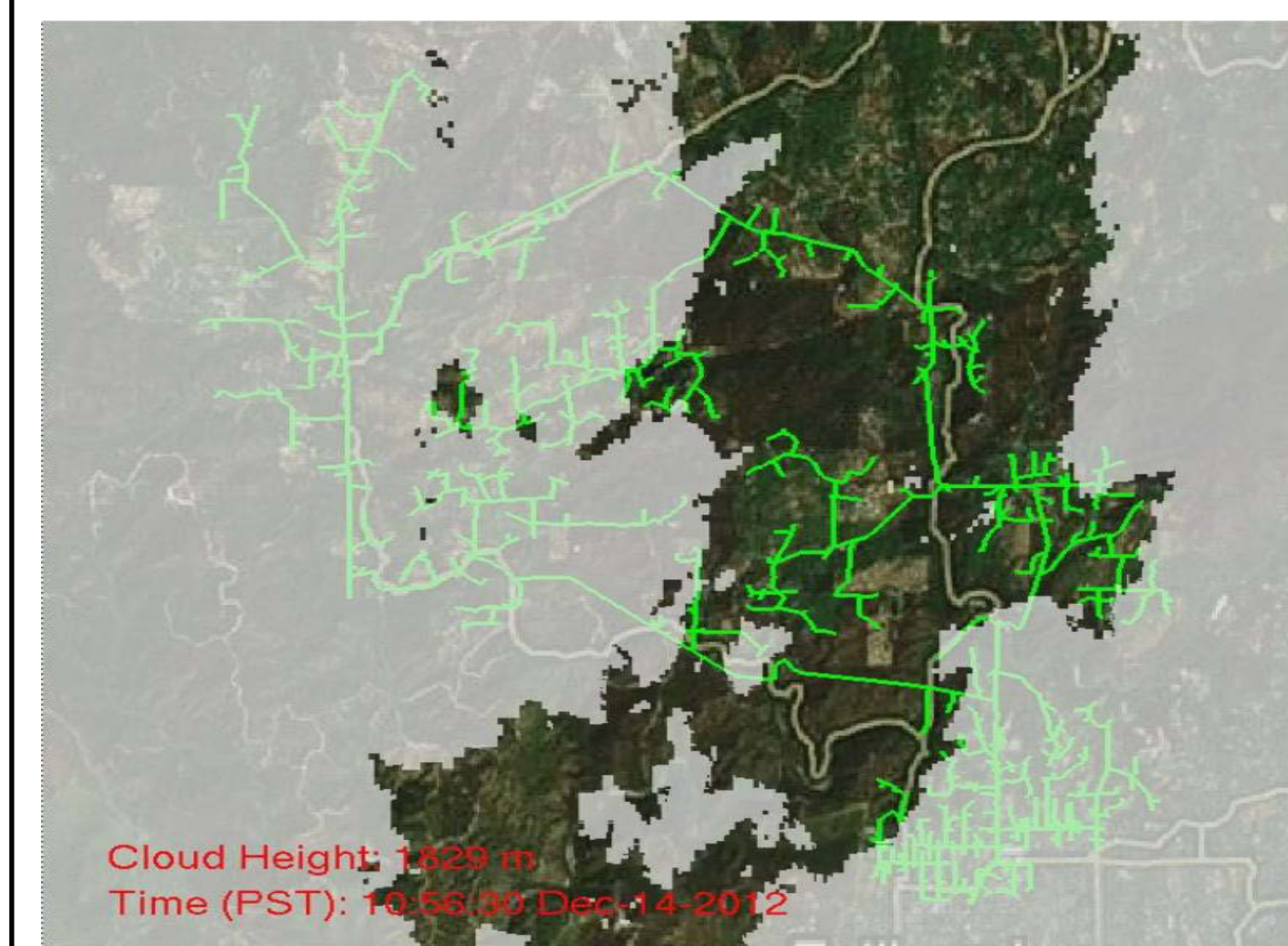
Results in table below shows that the incorporation of forecast data was shown to dramatically increase system lifetime (6 years extra) and its lifetime profit (360% increase on a 31 kWh storage system).

Local Vol-Var Control for PV Inverters

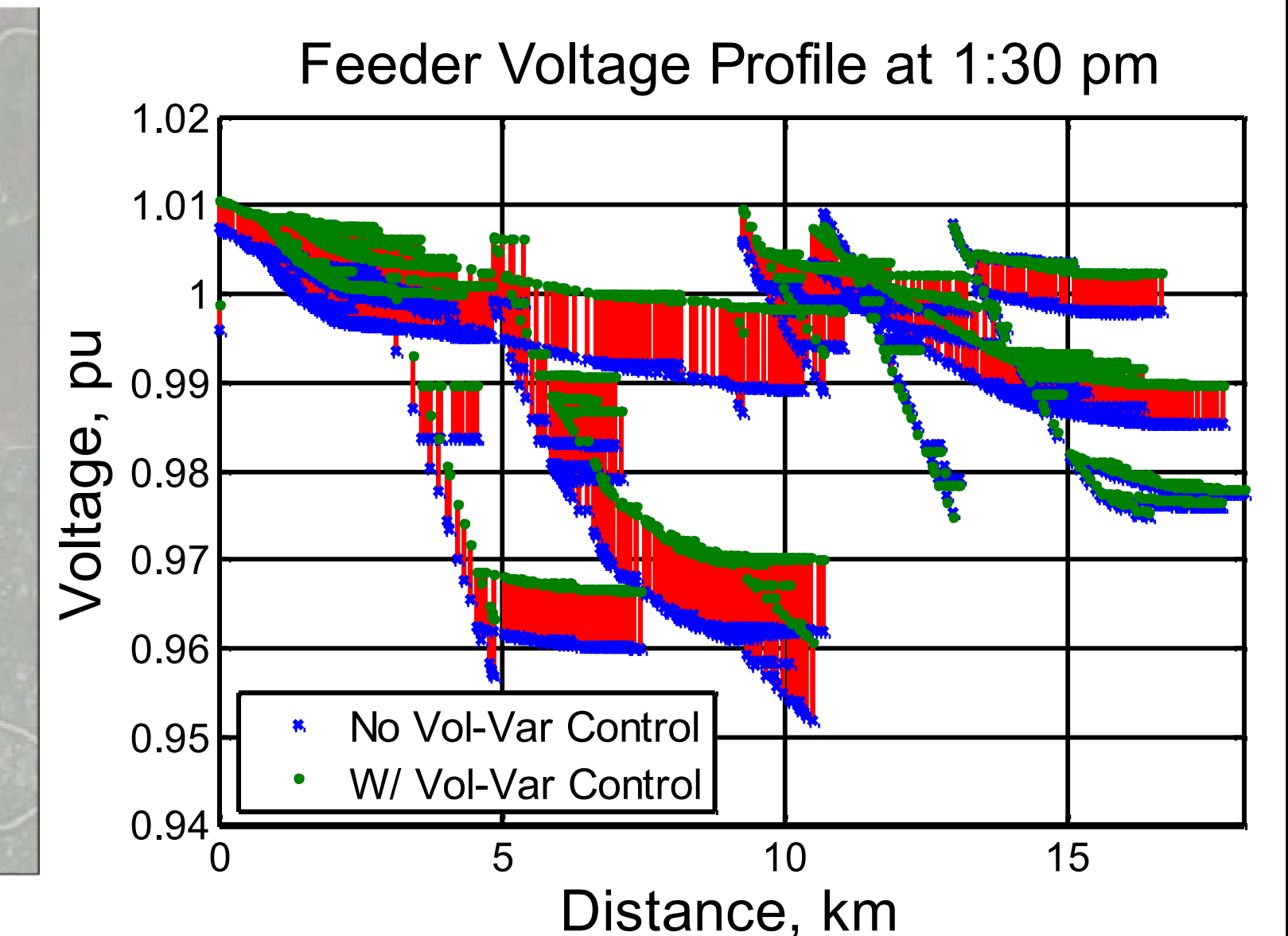
By combining USI-forecast and distribution system simulation using OpenDSS, we were able to design and demonstrate the impact of local volt-var control on the distribution network. With appropriate control design, the use of PV inverter reactive support will lessen the adverse impact of high PV penetration.



Local Vol-Var Control Scheme



Cloud cover simulation on SDGE feeder using sky imager forecast. The green lines are feeder distribution lines. Whitish area is covered by cloud.



Local Volt-Var control helps to bring the voltage level of the whole feeder up. The red lines show the increase in voltage levels along the feeder.

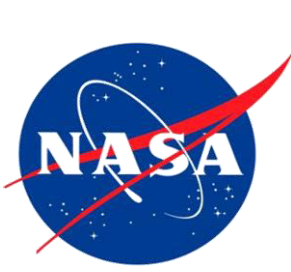
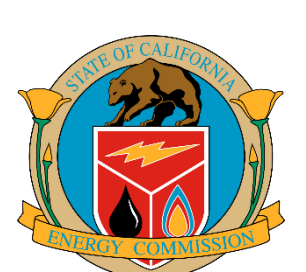
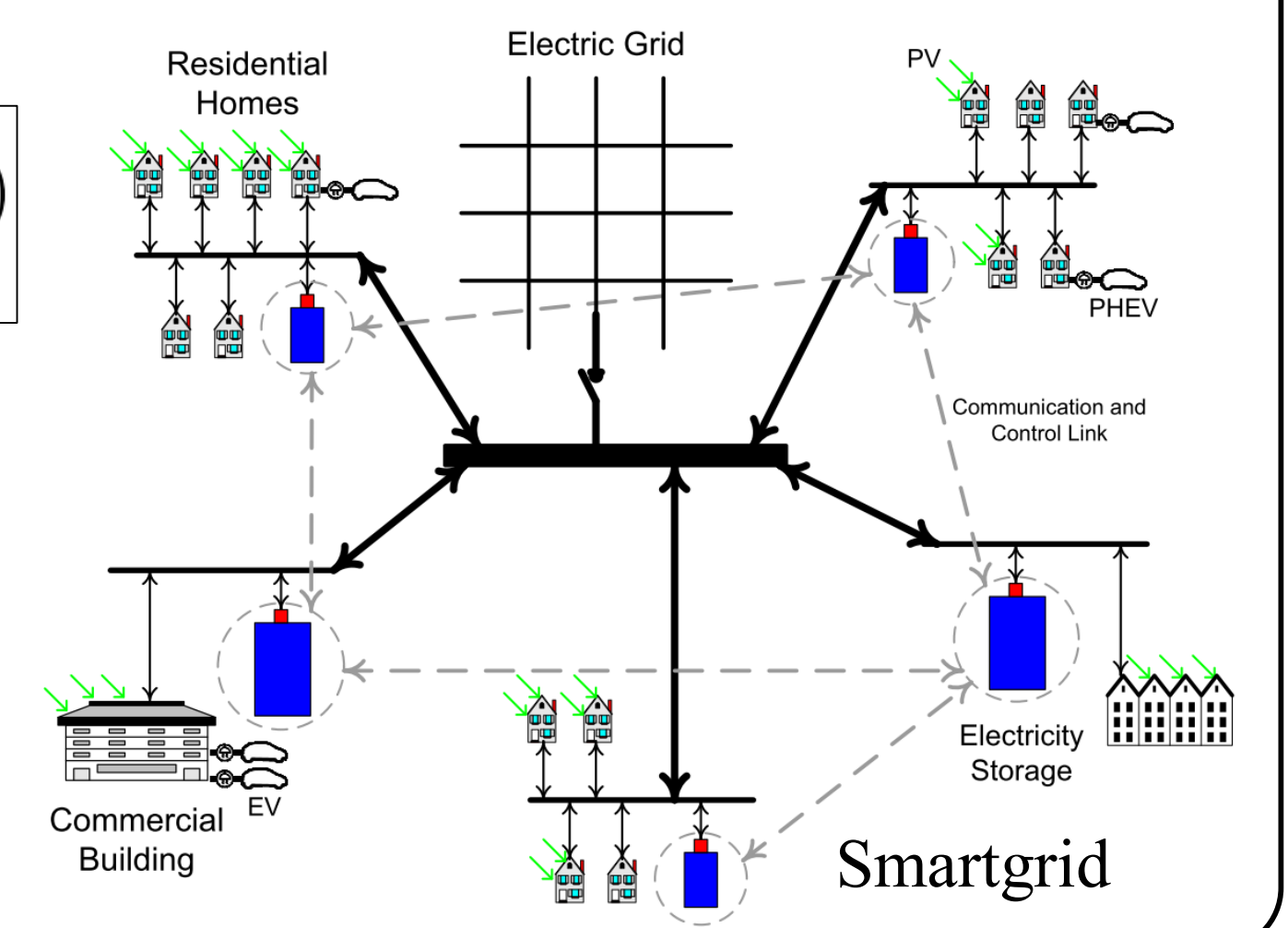
Centralized and Distributed Control for PV Inverters and ESSs

We are designing centralized and distributed control for multiple power inverters, storage systems, EV chargers, etc. for UCSD microgrid and SDGE feeders. The distributed control will (1) mitigate the impact of high penetration PV and (2) optimize the communication and interaction between all devices in smart grid setup.

$$\text{Cost: } J(u) = \sum_{t \in \tau} (J_{\text{loss}}(u(t)) + \delta J_{\text{power}}(u(t)))$$

Optimization Problem:

$$\begin{aligned} & \min_{q_G, v} J \\ & \text{s.t. } \forall t \in \tau \begin{cases} U_{\min} \leq \|u_l(t)\|_C \leq U_{\max}, & \forall l \in G, \\ V_{\text{dis}}^l \leq v_l(t) \leq V_{\text{ch}}^l, & \forall l \in G \cup S, \\ 0 \leq x_l(0) + \frac{1}{\beta_l} \sum_{s=1}^T v_l(s) \leq 1, & \forall l \in G \cup S, \\ \text{Power flow equations hold} \end{cases} \end{aligned}$$



Power System Restoration With Transient Stability

Terrence W.K. Mak, Hassan Hijazi, and Pascal Van Hentenryck

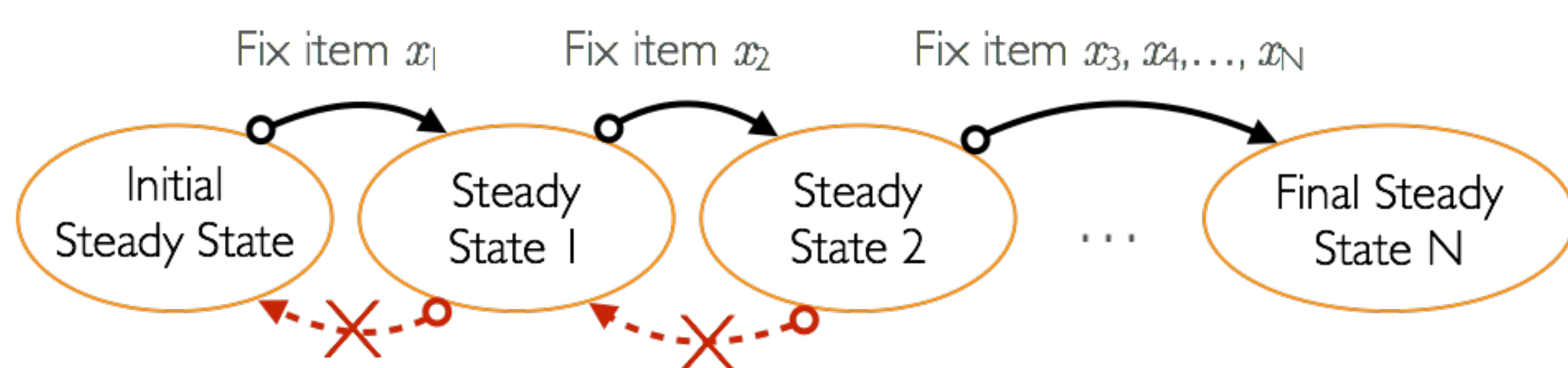
Power System Restoration

- Why? Natural disasters, infrastructure ageing, operator errors ...
- Outcome: A city could be in a total blackout



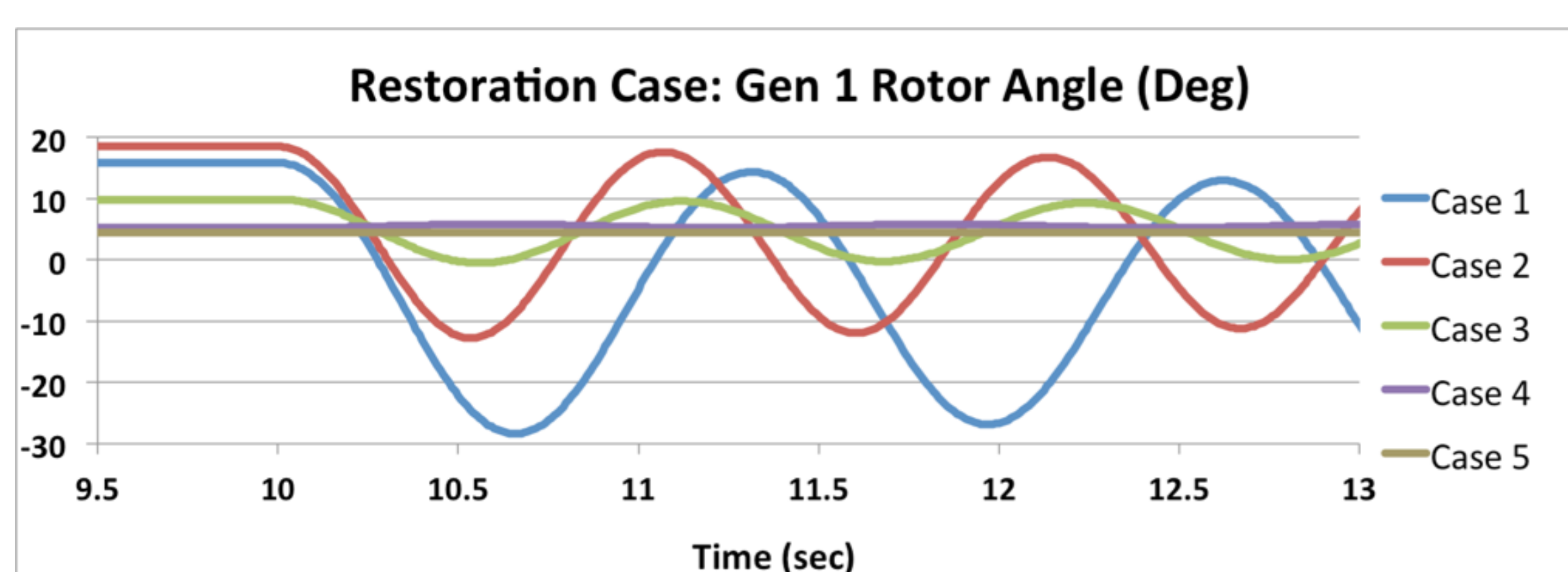
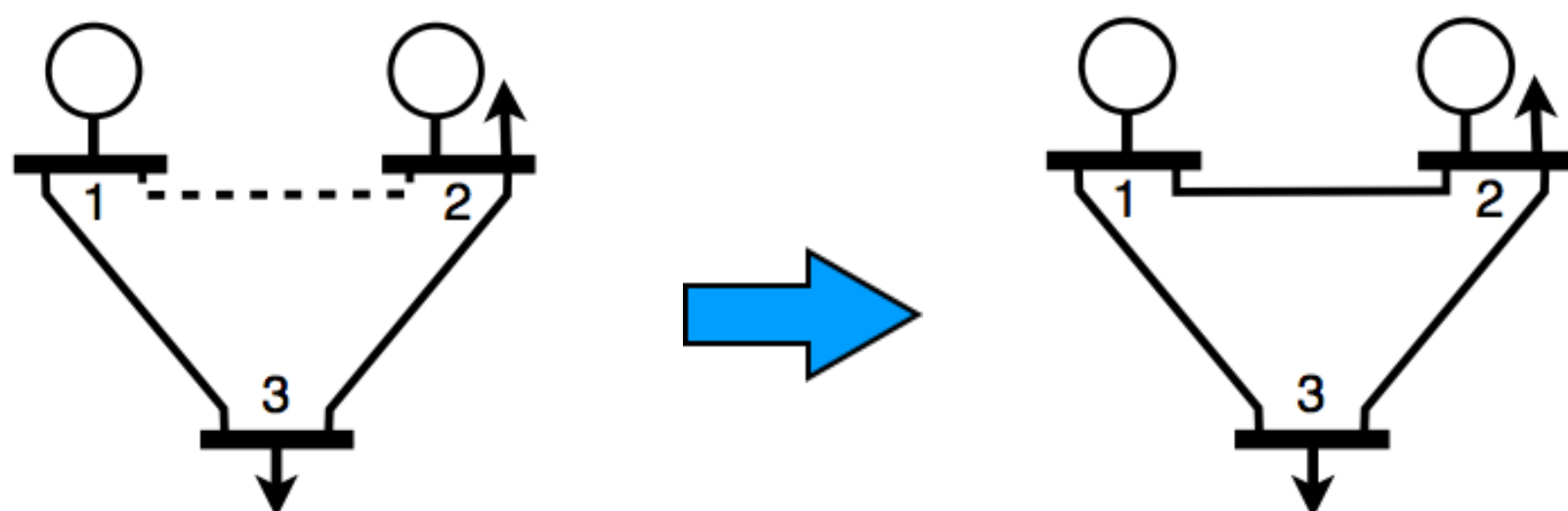
Restoration Ordering Problem

- Goal: Compute the best restoration ordering $[x_1, x_2, x_3, \dots, x_N]$ of damaged items such that loads could be brought up as quickly as possible [PSCC'11]



Transient Stability Assumption

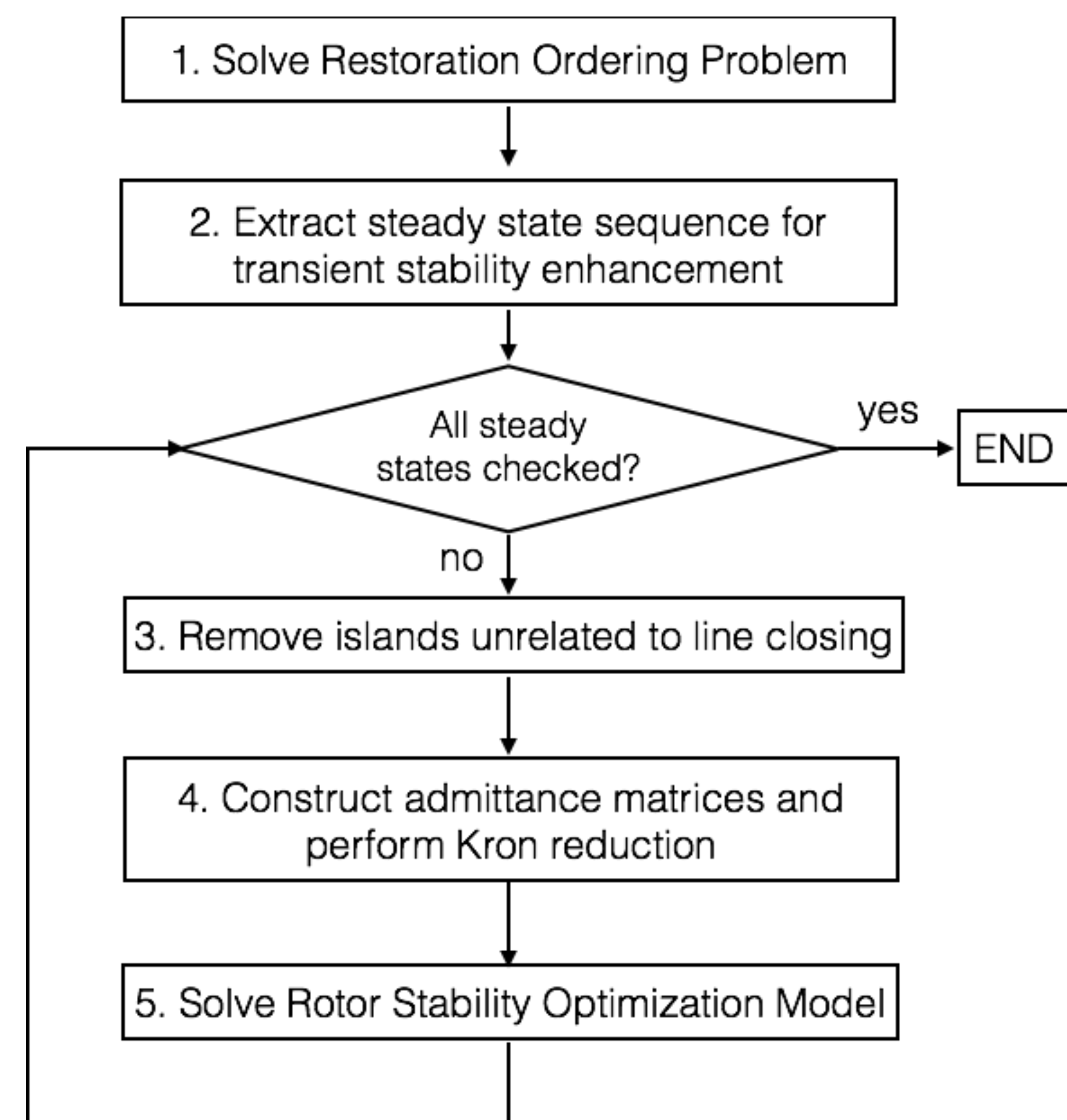
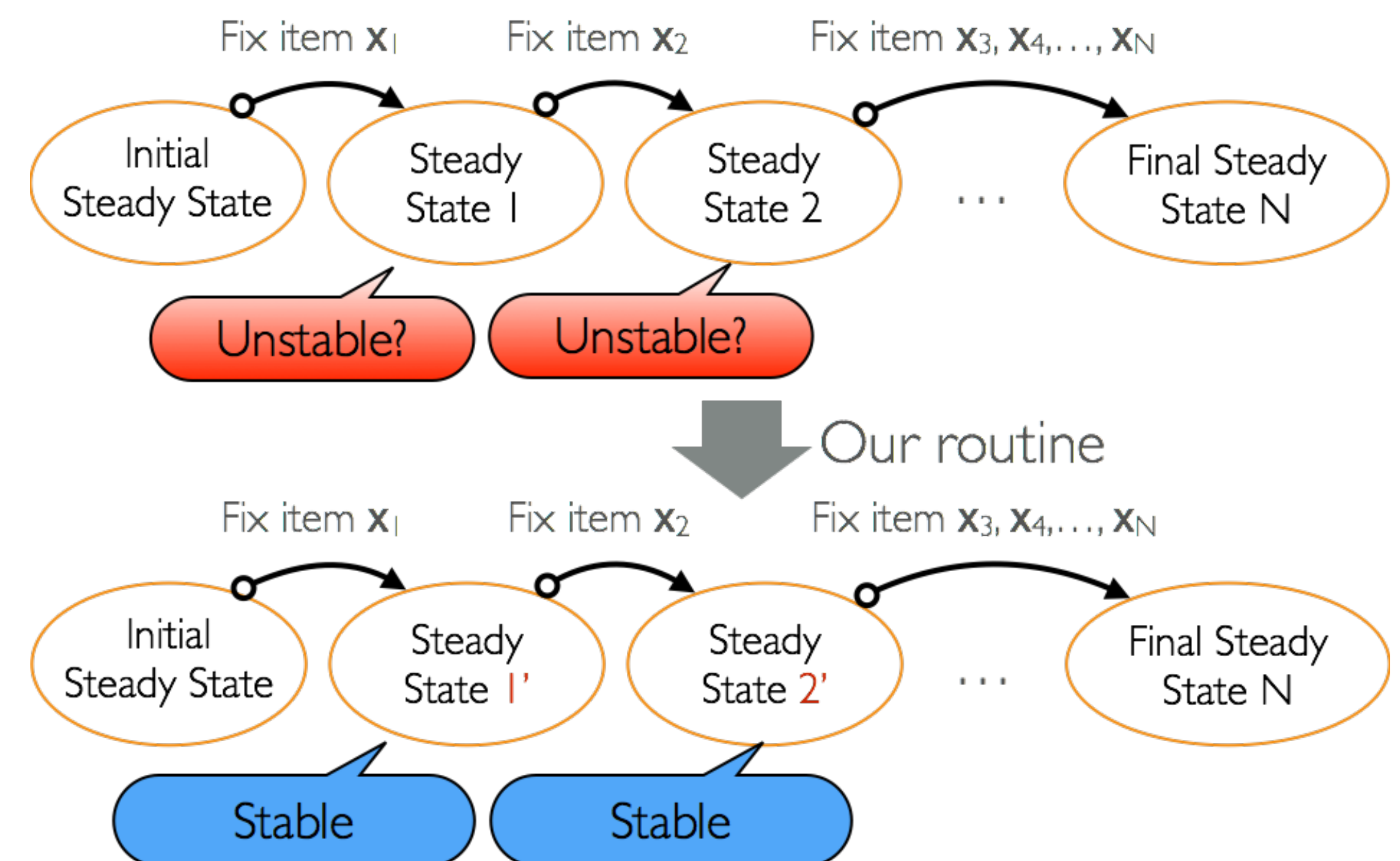
- Assumption: Traversing from one steady state to the other must always be feasible
- What we know: Different generator dispatches will have different rotor stability [PSCC'14]



Case	Bus 1	Bus 2	Bus 1	Bus 2	Gen 1 Pow.	Gen 2 Pow.	1st Swing
	Volt. (kV)	Volt. (kV)	Ang. (deg)	Ang. (deg)	(MW/Mvar)	(MW/Mvar)	(deg)
1	146.28	97.24	0.00	-47.58	221.12/143.46	20.00/18.00	44.229
2	146.28	146.28	0.00	-35.33	207.42/28.05	20.00/78.32	31.249
3	146.28	141.725	0	-12.14	102.59/10.66	102.59/10.66	10.385
4	146.28	123.84	0.00	0.00	61.05/48.08	143.85/-30.00	0.619
5	146.28	146.28	0.00	0.00	45.37/6.10	157.31/3.16	0.002

Stability Enhancement Routine

- Research goal: Given a restoration order, can we guarantee rotor stability?



- Challenge: Rotor swings are governed by 1st order differential equations.
- We design a non-linear model including generator dispatches to minimize the rotor swings [AAAI'15]

Experimental Results

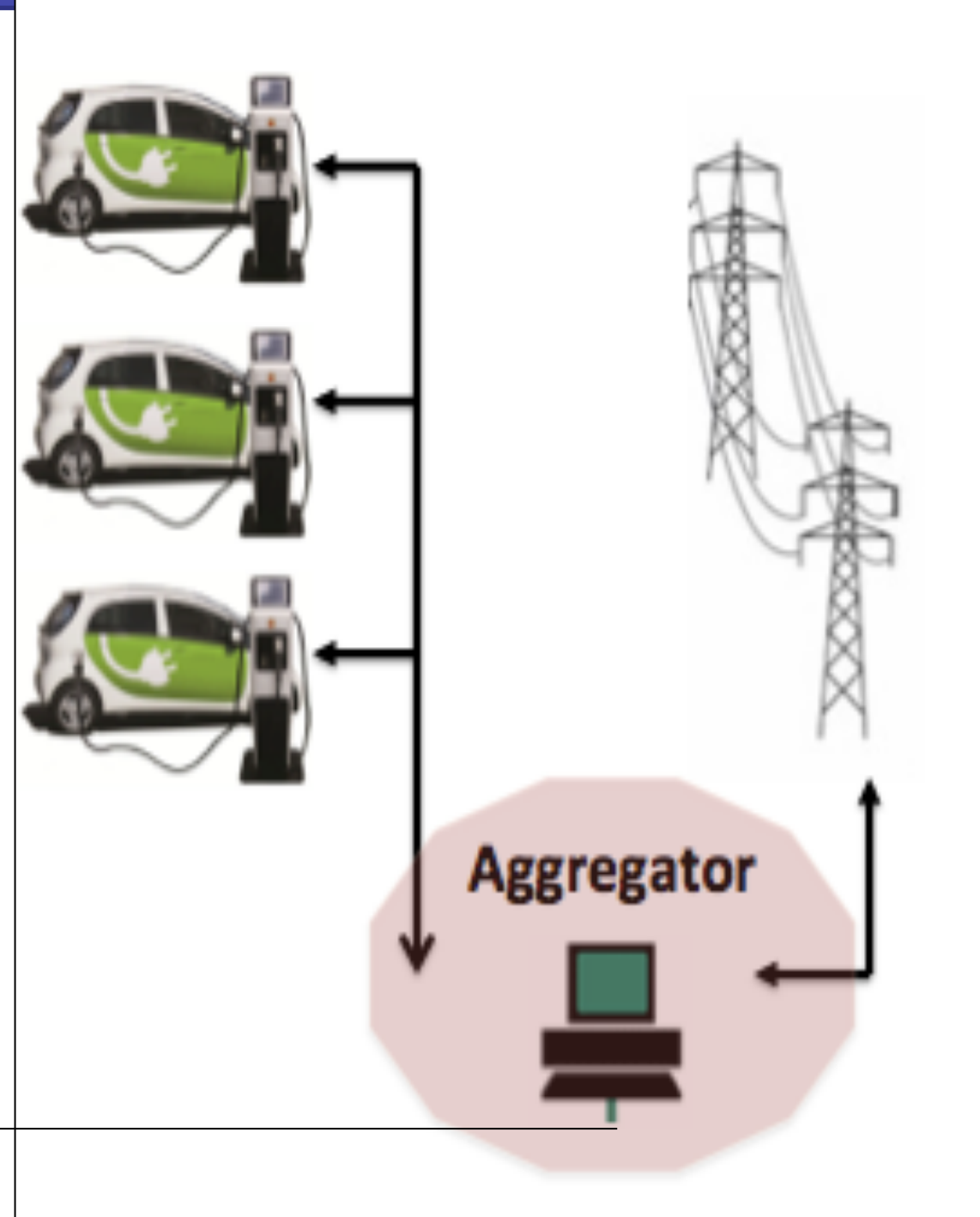
- Study: whether the steady states returned by the ROP are transient-stable
- Measure: Minimum change in generator dispatches to ensure transient stability
- Benchmarks: 6, 14, 30, 39, 57 bus from MATPOWER
- Implementation: AMPL with IPOPT 3.11

6 Bus					14 Bus				30 Bus				
		Maximum Rotor Swing			Maximum Rotor Swing				Maximum Rotor Swing				
Gen.	Reactance	90	40	10	1	90	40	10	1	90	40	10	1
	0.02	0.00002	0.00002	0.00002	0.17967	0.00000	0.00000	0.00000	6.53902	0.00004	0.00003	0.00004	2.91547
	0.06	0.00003	0.00003	0.00003	0.10593	0.00000	0.00000	0.00000	8.67193	0.00004	0.00003	0.00004	3.07084
	0.10	0.00003	0.00002	0.00002	0.00843	0.00000	0.00000	0.00000	8.18311	0.00004	0.00004	0.00004	3.76922
	0.14	0.00002	0.00003	0.00002	0.30335	0.00000	0.00000	0.00000	6.09923 (1)	0.00004	0.00005	0.00004	4.17696
	0.20	0.00003	0.00003	0.00003	1.01248	0.00000	0.00000	0.00000	3.66457 (3)	0.00004	0.00004	0.00004	4.07680
39 Bus					57 Bus								
		Maximum Rotor Swing			Maximum Rotor Swing								
Gen.	Reactance	90	40	10	1	90	40	10	1				
	0.02	0.00001	0.00001	20.52951	7.95879 (6)	0.00000	0.00000	0.66260	131.39311				
	0.06	0.00001	0.00001	81.80927 (1)	0.00002 (7)	0.00000	0.00000	1.36766	1.12417 (21)				
	0.10	0.42052	0.28436 (1)	78.24781	48.13747 (5)	0.23766	0.23766	39.33088	1.14312 (21)				
	0.14	0.49691	0.49698	60.35684	41.99449 (5)	0.68299	0.67222 (1)	73.84672	1.26118 (21)				
	0.20	0.00002	0.00002	34.26957	69.35875 (3)	0.83704	0.83744	120.01411 (1)	1.41655 (21)				

Abstract

Vehicle-to-grid (V2G) capable Plug-in Electric Vehicles (PEV) communicates with the grid, stores energy, and can return energy to the electric grid. We develop a novel modeling approach, which is based on a system of partial differential equations (PDEs), to aggregate and control large populations of PEVs. This framework is very well suited and computationally efficient to address tomorrow's challenge of designing the best strategies for PEV smart charging. First, we validate our model on the Vehicle-to-grid simulator (V2G-Sim). Then we demonstrate that this approach can be used to manage fleets of vehicles and permit a PEV aggregator to participate in the regulation market (provide energy to the grid), and supply PEV drivers with sufficient charge.

Objective



- ◆ Develop an aggregation model for large fleets of electric vehicles
- ◆ Design a smart control algorithm to participate in the regulation market
- ◆ Satisfy drivers' needs for mobility

Design a combined smart-charging method for thousands / millions of Electric Vehicles

Prepare the country for the Transportation revolution
Facilitate emergence of V2G aggregators

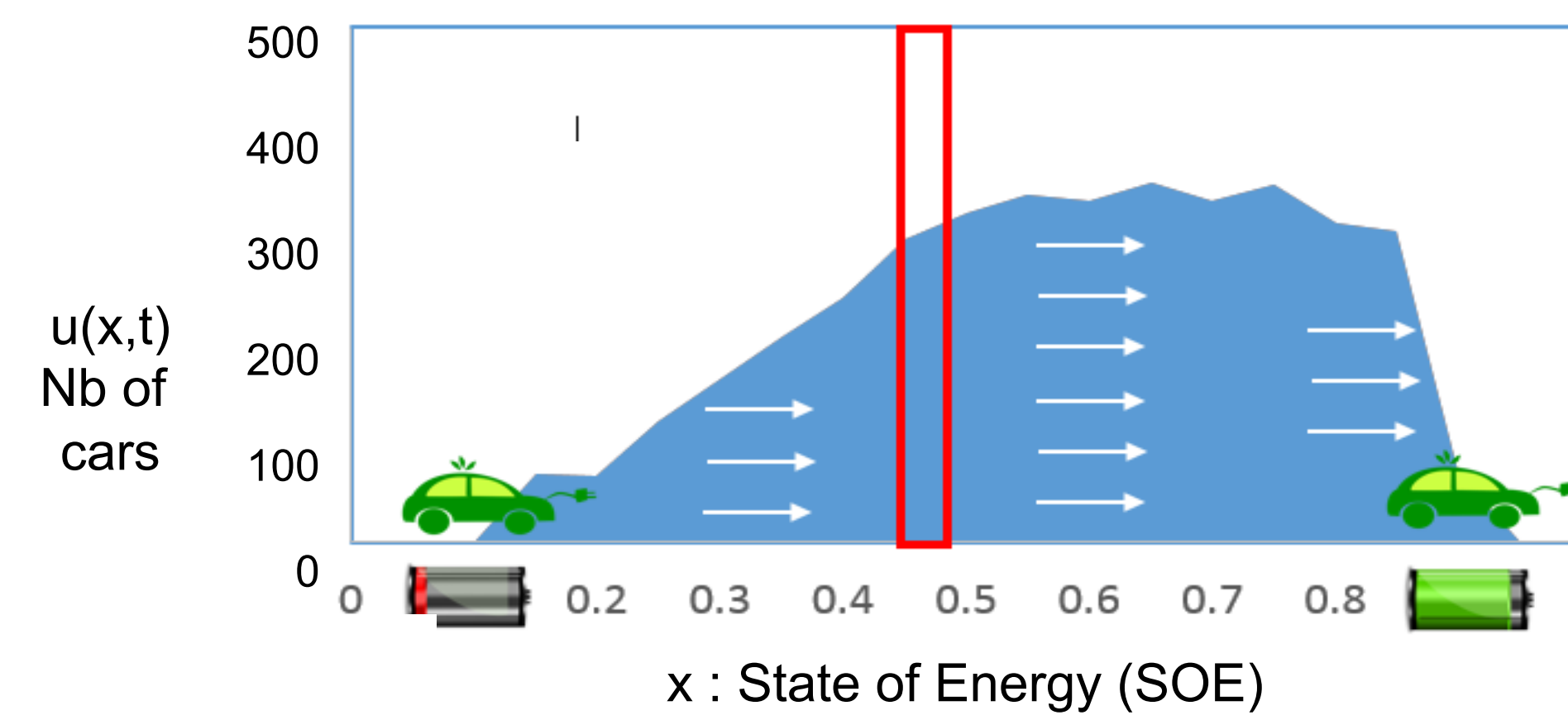
Optimal Charging of Vehicle-to-Grid Fleets via PDE Aggregation Techniques

Caroline Le Floch, Florent di Meglio, Scott Moura



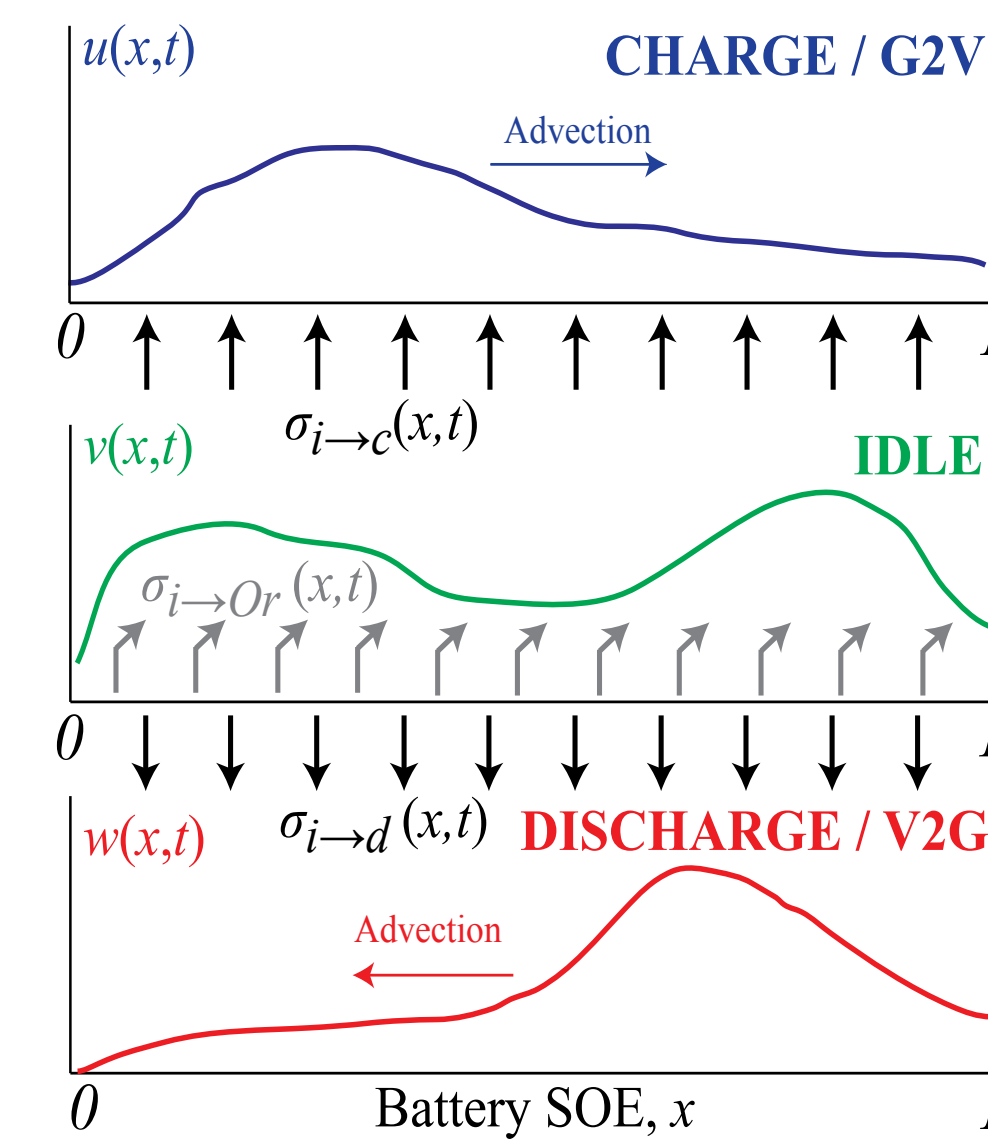
Modeling aggregation of PEVs

Transport Based model



Vehicles charge at rate $q_c(x,t)$
External flows of vehicles (from road) $\sigma_{i \rightarrow c}(x,t)dt$.
$$[u(x,t+dt) - u(x,t)]dx = q_c(x,t)u(x,t)dt - q_c(x+dx,t)u(x+dx,t)dt + \sigma_{i \rightarrow c}(x,t)dx$$
 (6)

Vehicle-To-Grid Framework



The aggregator controls the number of vehicles in each state:

- G2V: charging $u(x,t)$
- Idle $v(x,t)$
- V2G: discharging $w(x,t)$ (sells energy)

Coupled system of PDEs:

$$\begin{aligned} \frac{\partial u}{\partial t}(x,t) &= -\frac{\partial}{\partial x}[q_c(x,t)u(x,t)] + \sigma_{i \rightarrow c}(x,t), \\ \frac{\partial v}{\partial t}(x,t) &= -\sigma_{i \rightarrow or}(x,t) - \sigma_{i \rightarrow c}(x,t) - \sigma_{i \rightarrow d}(x,t), \\ \frac{\partial w}{\partial t}(x,t) &= \frac{\partial}{\partial x}[q_d(x,t)w(x,t)] + \sigma_{i \rightarrow d}(x,t). \end{aligned}$$

Validation

V2G-Sim is an agent-based simulator that models the driving and charging behavior of individual PEVs. It is developed by the Grid Integration Group at LBNL.

Data: 17805 vehicles in California during a week-day from National Household Travel Survey (NHTS) 2009. The fleet is composed of Nissan Leaf cars.



2 control cases : Open-Loop / Discharge during electricity peak hours
2 charging rates : L1 chargers (1.44kWh) / L2 chargers (6.6kWh)

$$e(t) = \frac{\| (u+v+w)PDE(\cdot,t) - (u+v+w)V2Gsim(\cdot,t) \|_2}{\| (u+v+w)V2Gsim(\cdot,t) \|_2}$$

Case	Mean error
Open Loop L1 charger	1.1%
Open Loop L2 charger	2.3%
V2G control L1 charger	0.2%
V2G control L2 charger	2.8%

Optimal control of vehicles

Choose the best flows between G2V, V2G and Idle (minimize aggregator cost) such that: every driver is satisfied and the aggregator supplies energy to the regulation market. Main assumptions:

- Electricity cost C_{elec} , departures Dep , regulation power P^{des} are known one day in advance.
- Cars must depart with minimum SOE X_{dep} .

Control Formulation

$$\min_{u,v,w,Dep} \Delta t \Delta x \sum_{n=0}^N \sum_{j=0}^J C_{elec}^n q_j^n w_j^n$$

subject to

$$[u+v+w]^{n+1} + \frac{Dep^{n+1}}{\Delta x} = M_c u^n + M_d w^n + \frac{Arr^{n+1}}{\Delta x}$$

$$u_0^n = 0, \quad v_j^n = 0, \quad w_j^n = u_{0,j}(j\Delta x), \quad v_j^n = v_{0,j}(j\Delta x), \quad w_j^n = w_{0,j}(j\Delta x), \quad \forall j,$$

$$\begin{aligned} u^n, v^n, w^n, Dep^n &\geq 0, \\ u_j^n &= 0 \quad \forall j \geq X_{max} \cdot J \\ v_j^n &= 0 \quad \forall j \leq X_{min} \cdot J \\ w_j^n &= 0 \quad \forall j \leq X_{min} \cdot J \end{aligned}$$

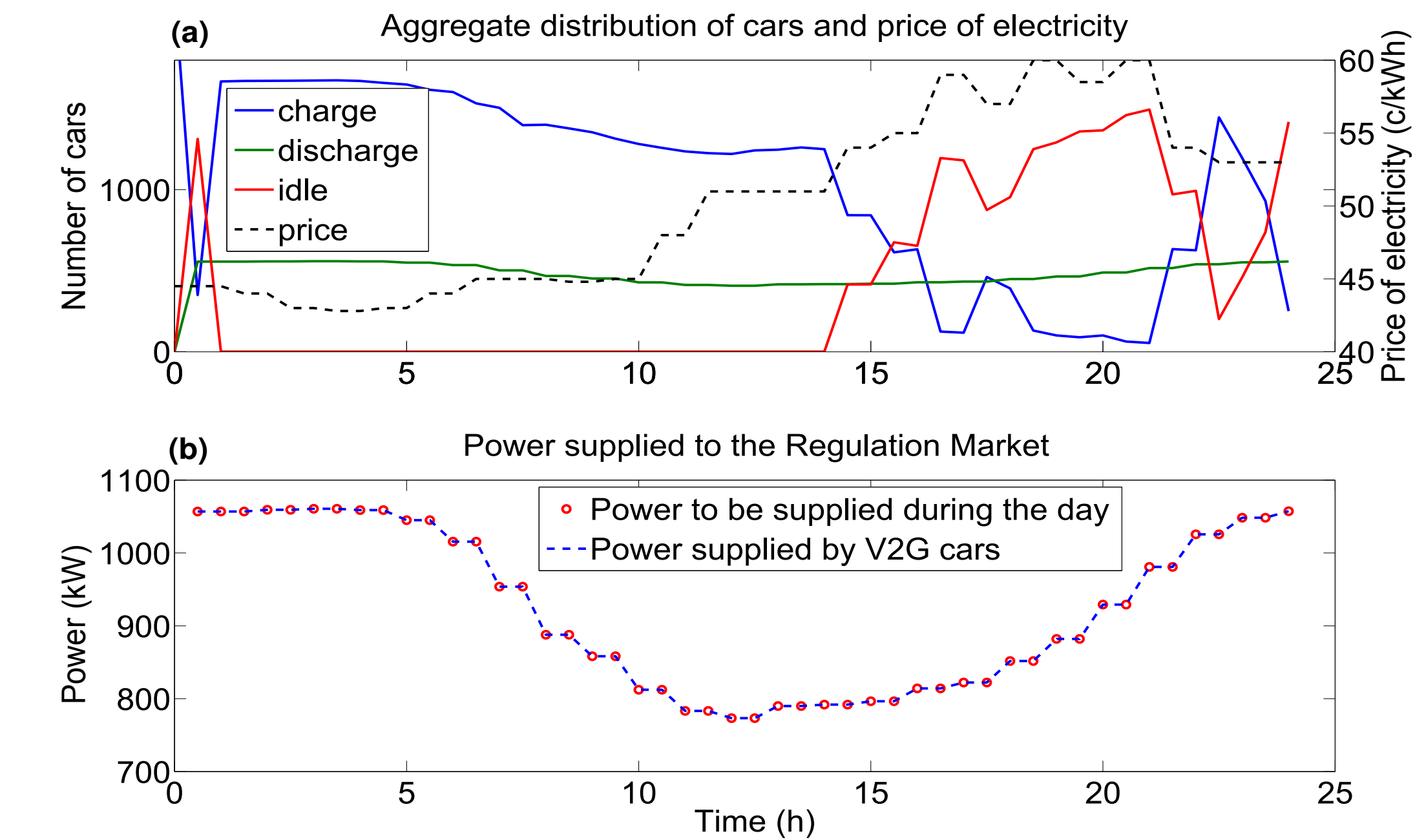
$$\Delta x \sum_{j=0}^J q_{d,j}^n w_j^n \geq P^{des,n}$$

$$\begin{aligned} \sum_{j=X_{dep} \cdot J}^J Dep_j^n &= Dem^n \\ \Delta x \sum_{j=X_{dep} \cdot J}^J u_j^n + v_j^n + w_j^n &\geq N_{min} \end{aligned}$$

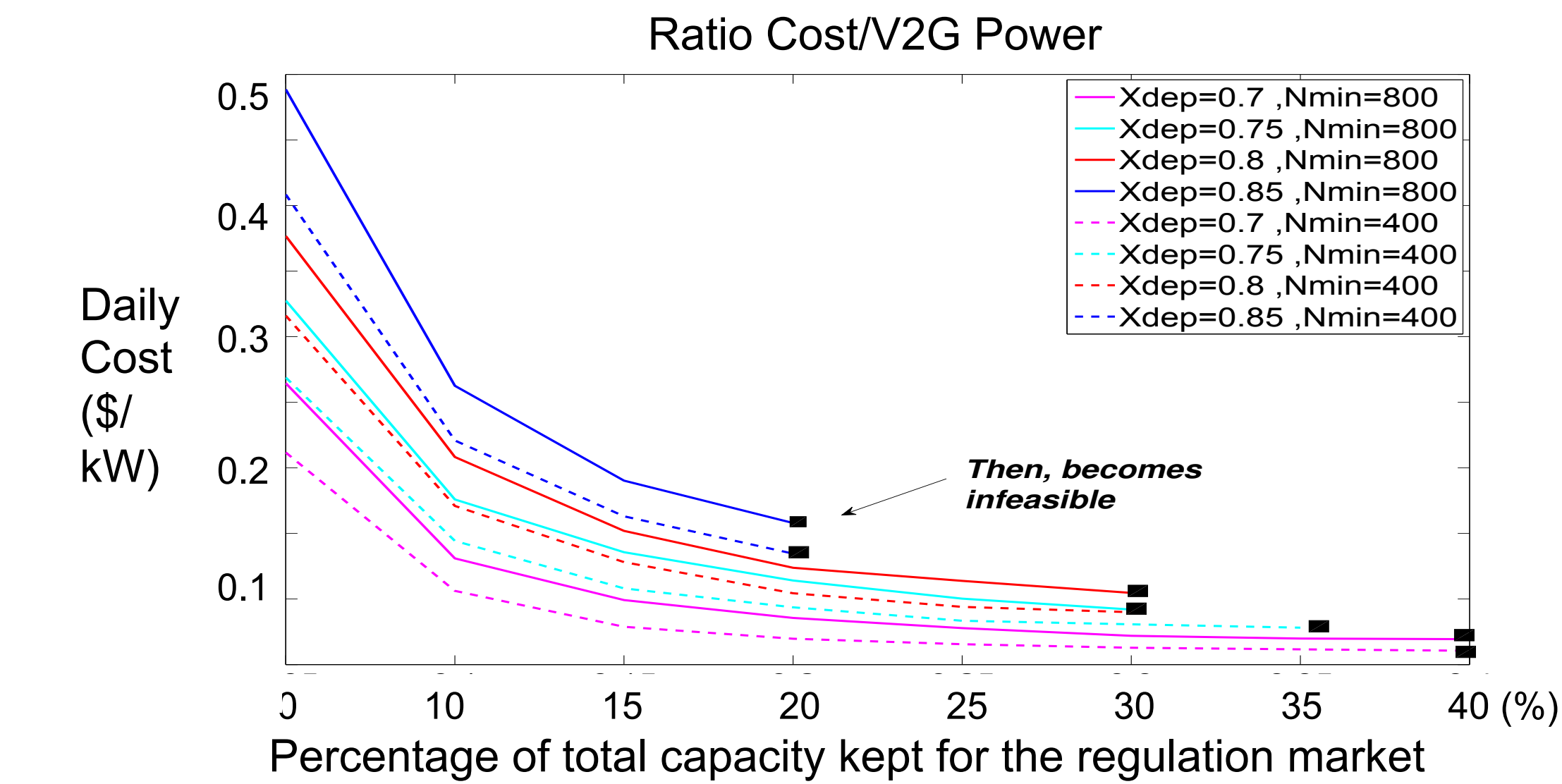
After discretization of PDEs, we formulate the Linear Program above, and solve it using a LP solver.

- Time horizon: 24h
- Number of cars: 2300 (taken from NHTS)
- Charging rate: 1.9kWh

Result and sensitivity analysis



- The aggregator computes flows between idle and G2V: EVs charge when price of electricity is lower.
- V2G cars supply required energy to the grid.



- The optimization allows economies of scale: cost per produced kW decreases as required energy increases.

Conclusion

- ◆ The model is validated, PDE techniques are well suited for large populations of Evs.
- ◆ The optimization program allows EV aggregators to optimize their cost while participating to the regulation market and satisfy every driver.

◆ How can we integrate grid constraints into this framework?

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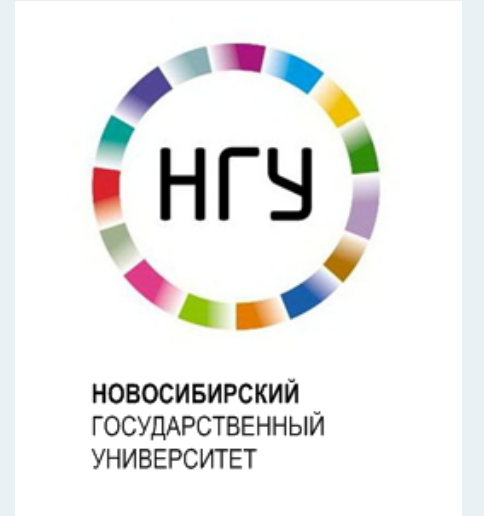
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Island Russkiy - test field for the research of emergency control in microgrids

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Introduction

Russian power system doesn't have any test fields for study and development of scientific, technological and economic solutions in microgrids and virtual power plants (VPP). This fact stops the work on implementing modern technologies on electricity generation, distribution and consumption. However, this topic is one of the prioritized in Europe and US. Taking into account convenient geographical position of Island Russkiy and recently renewed energy infrastructure, as well as potential for solar and wind energy, one can find the island very perceptive, unique test field for experiments and research in microgrids.

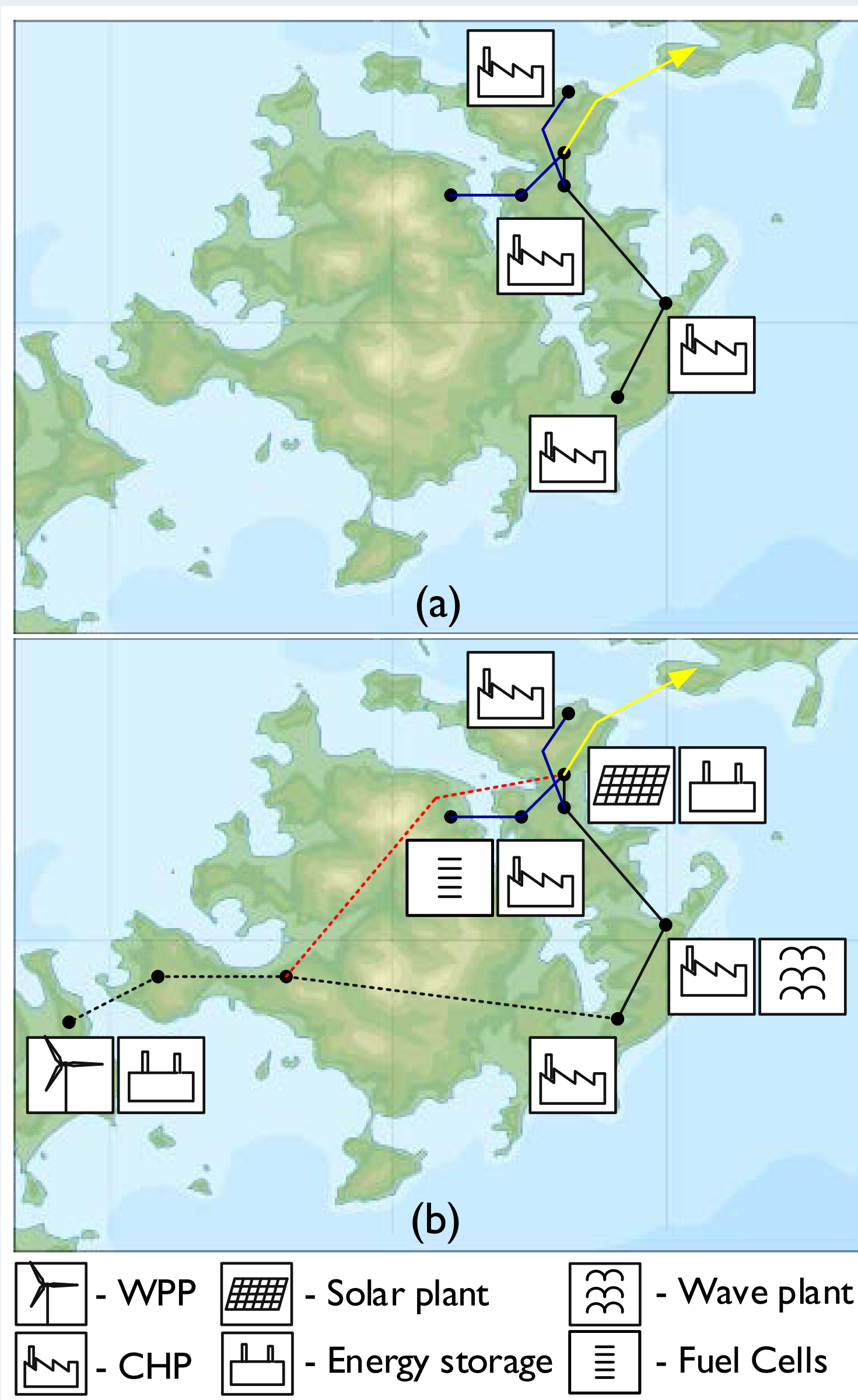


Figure 1 – Possible stages of power system development on the Island.
Solid lines – existing power lines, dashed lines – possible lines.
Voltage levels: yellow color – 220 kV, red – 100 kV, black – 35 kV, blue – 10 kV.

Methods

The purpose of the work is to test possible smart grid components, such as energy storage devices, for emergency control in the microgrid power system. To do this an adequate mathematical model of Island Russkiy's power system is required.

Thus the first stage was focused on model creation and validation. The base regime is designed so there is a power flow from the main grid to the Island. Then, the following test was set:

Trip of the 220 kV overhead line that connects the Island to Primorskaya power system. The microgrid will operate in islanded mode.

The intent is to show the frequency control possibilities of an energy storage device as well as power oscillations damping during lack of generation.

Model description

Island Russkiy's power system consists of four combined heat and power plants (CHPs) that have rated capacity from 2.8 to 28.4 MWe (see [1-3] for details) with total rated capacity on the island of 45 MWe.

Generation voltage level is 10 kV and all power plants are connected by 35kV radial cable lines. The microgrid has connection to the mainland by 220 kV marine cable and overhead line, through substation (SS) Russkaya.

Centralnaya CHP is the biggest one with 6 installed gas turbines (28.4 MWe). The highest consumption is Far East Federal University (35 MWe) and is located at the same node.

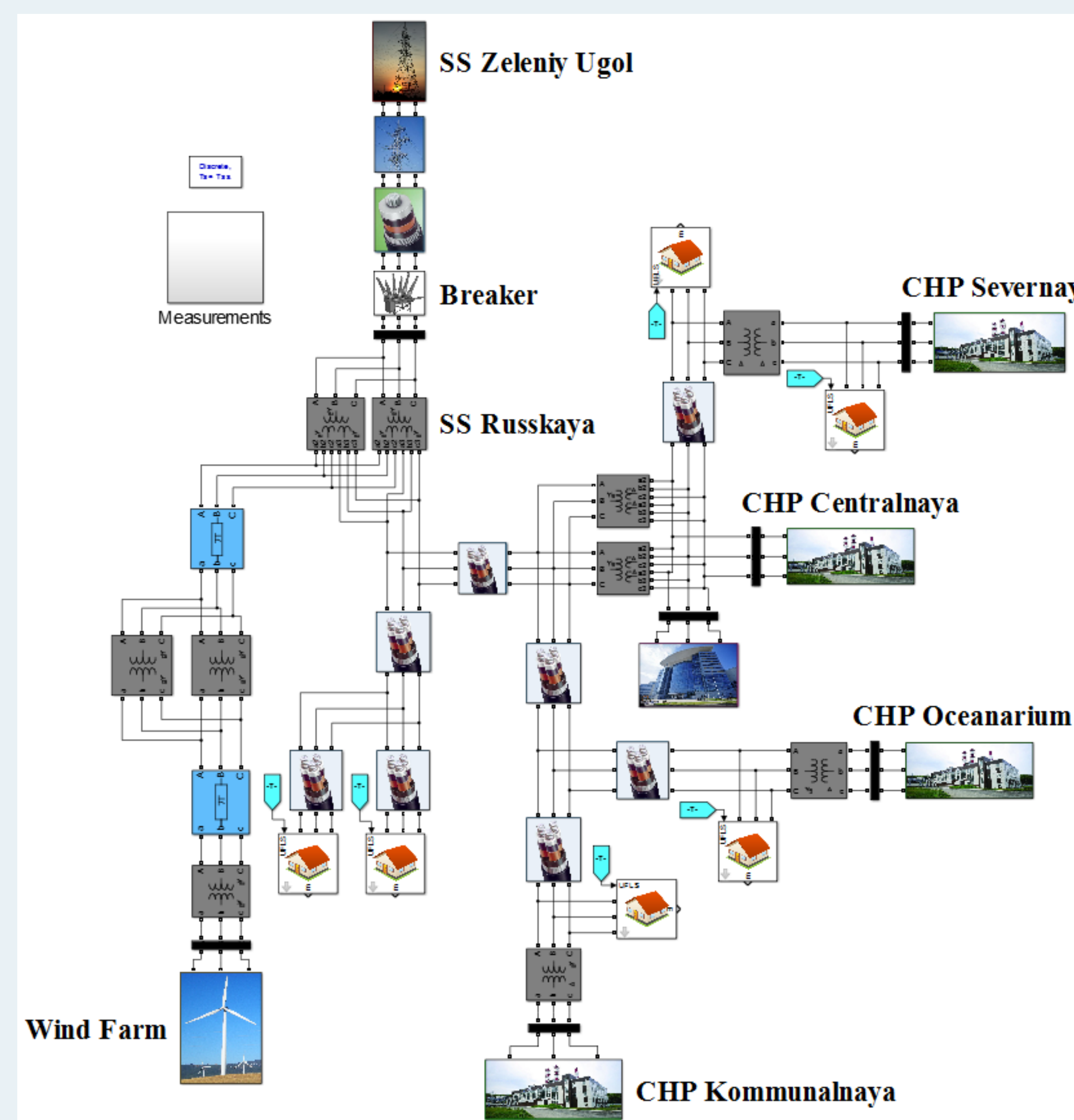


Figure 2 – MATLAB/Simulink model of the power system.

The model of the power system was created in EUROSTAG 5.1 as well as in MATLAB/Simulink. The first software was used for fast modelling of only electromechanical processes in the network. The second one was used for electromagnetic and electromechanical transients in more detailed model – it consists of full models of synchronous machines, Rowen's models for gas turbines [4] and energy storage device (ES) with on converter (figure 3). It was assumed that energy storage has rated capacity of 5 MWe and located on the Far East Federal University campus.

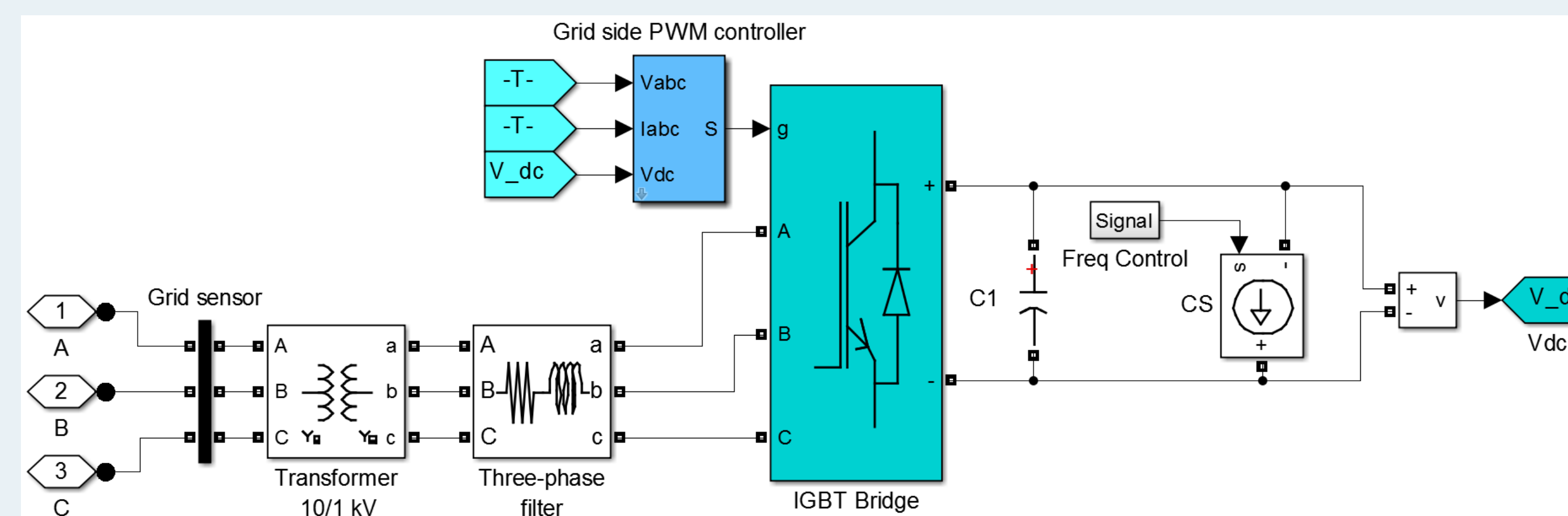


Figure 3 – MATLAB/Simulink model of the energy storage with AC/DC converter.

Results

For both models disconnection from the grid was simulated. One can see the results for EUROSTAG on figure 4 and for MATLAB/Simulink on figure 5. In both cases under frequency load shedding (UFLS) was modelled as a standard tool for emergency control [5]. Then a joint operation of UFLS and ES was studied.

It is clear that energy storage device can significantly improve the quality of transients. For example, there were no load shedding during operation, after the disturbance. Also the resulting low-frequency oscillations of gas turbines' power due to speed controller characteristics were quickly damped.

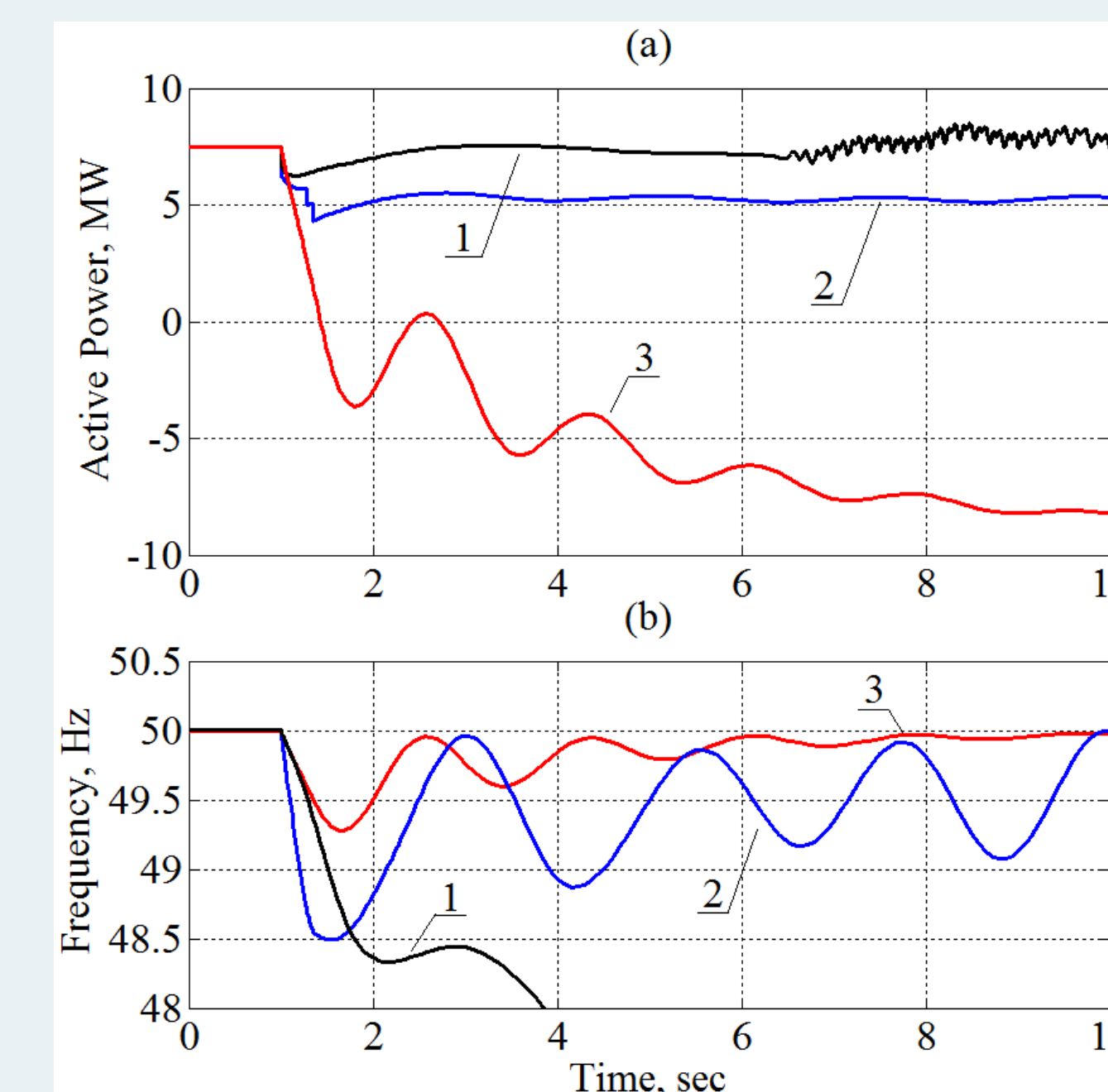


Figure 4 – Energy storage device active power (a) and frequency at the Centralnaya CHP node for EUROSTAG 5.1:
1) no control actions, 2) UFLS, 3) UFLS and ES

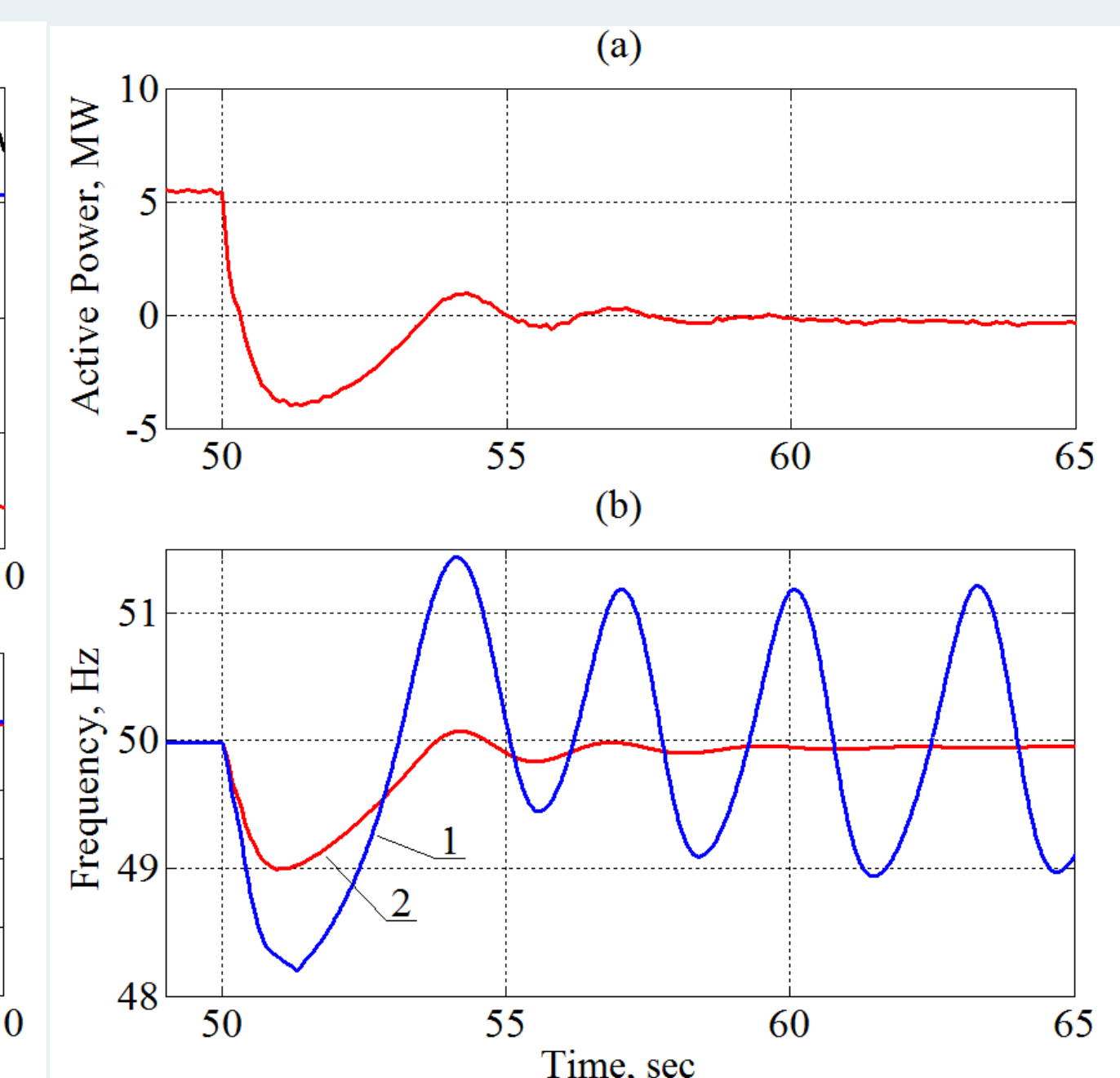


Figure 5 – Energy storage device active power (a) and frequency at the Centralnaya CHP node for MATLAB/Simulink:
1) UFLS, 2) UFLS and ES

Conclusions

The Russkiy Island may become one of the most convenient places for testing new technologies in Russian power system. This work presents one of the most probable network topologies. Two models were designed based on this network configuration – simplified EUROSTAG 5.1 model and relatively detailed MATLAB/Simulink.

The study was focused on application of energy storage device for frequency control in the system. The results for both models showed that with proper control ES can be highly effective for microgrid stability.

Recently, detailed information on the current structure on Island Russkiy power system was obtained, so future work will be dedicated to model detalization and validation.

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Approximate-Current Instanton Analysis: Detecting Vulnerability in the Power Grid

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Introduction

Renewable fluctuations add vulnerability to the power grid.

As renewable generation fluctuates about its forecast, power flows and voltage magnitudes throughout the grid undergo complicated shifts. Most variations are harmless, but even a seemingly benign perturbation can violate network constraints.

The instanton is the most likely generation pattern that violates a constraint.

Of all possible generation patterns, some violate network constraints. Of these, the most likely to occur is the instanton.

The nonlinear AC instanton problem has no guaranteed solution.

The accuracy of the AC instanton formulation has a price: the problem is non-convex and may not have a solution. This is unacceptable in a real-time environment.

The linear DC instanton problem has questionable accuracy.

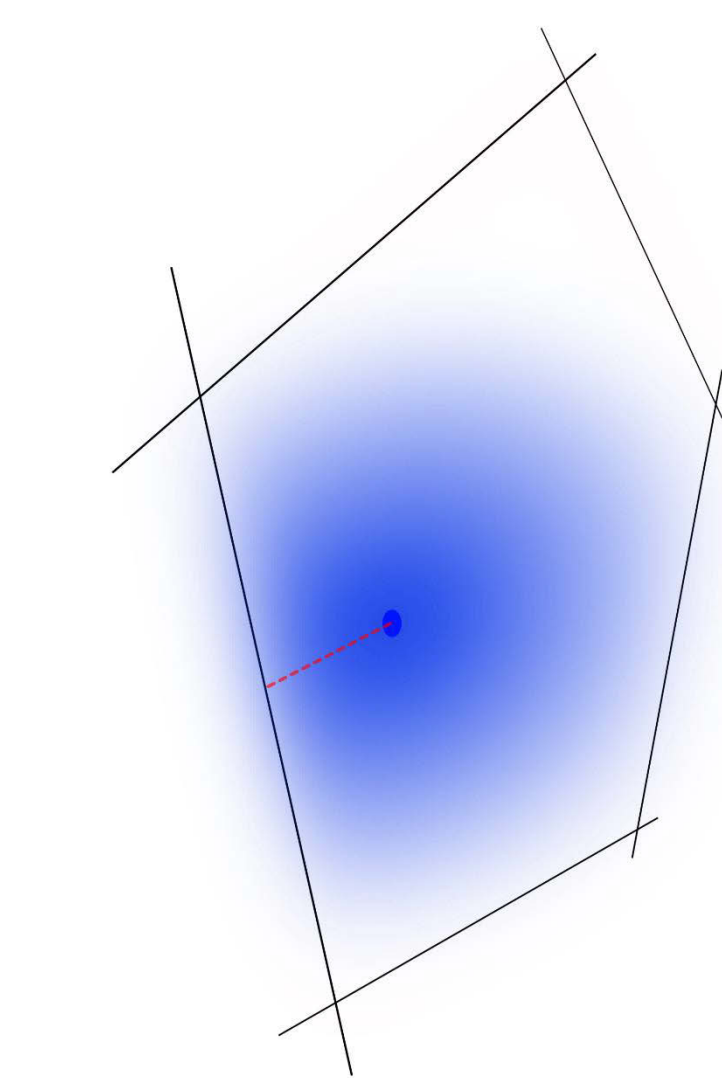
When the DC power flow approximation is applied to the instanton problem, an analytic solution may be found by matrix inversion. Because the instanton lies on a network constraint, however, DC assumptions (like flat voltage profile) are suspect.

Accommodating non-flat voltage profiles improves instanton accuracy.

The new method maintains convexity while accommodating non-flat voltage profiles and reactive power injections.

Objectives

- To use approximate AC methods to develop an instanton-finding tool with
 - greater accuracy than DC instanton method,
 - guaranteed convergence,
 - rapid solution time (sub-exponential in network size), and
 - insightful output (ranked list of extreme events, reconfiguration assistance)
- To characterize differences between DC and approximate AC instanton methods
- To understand differences between DC and approximate AC power flow methods

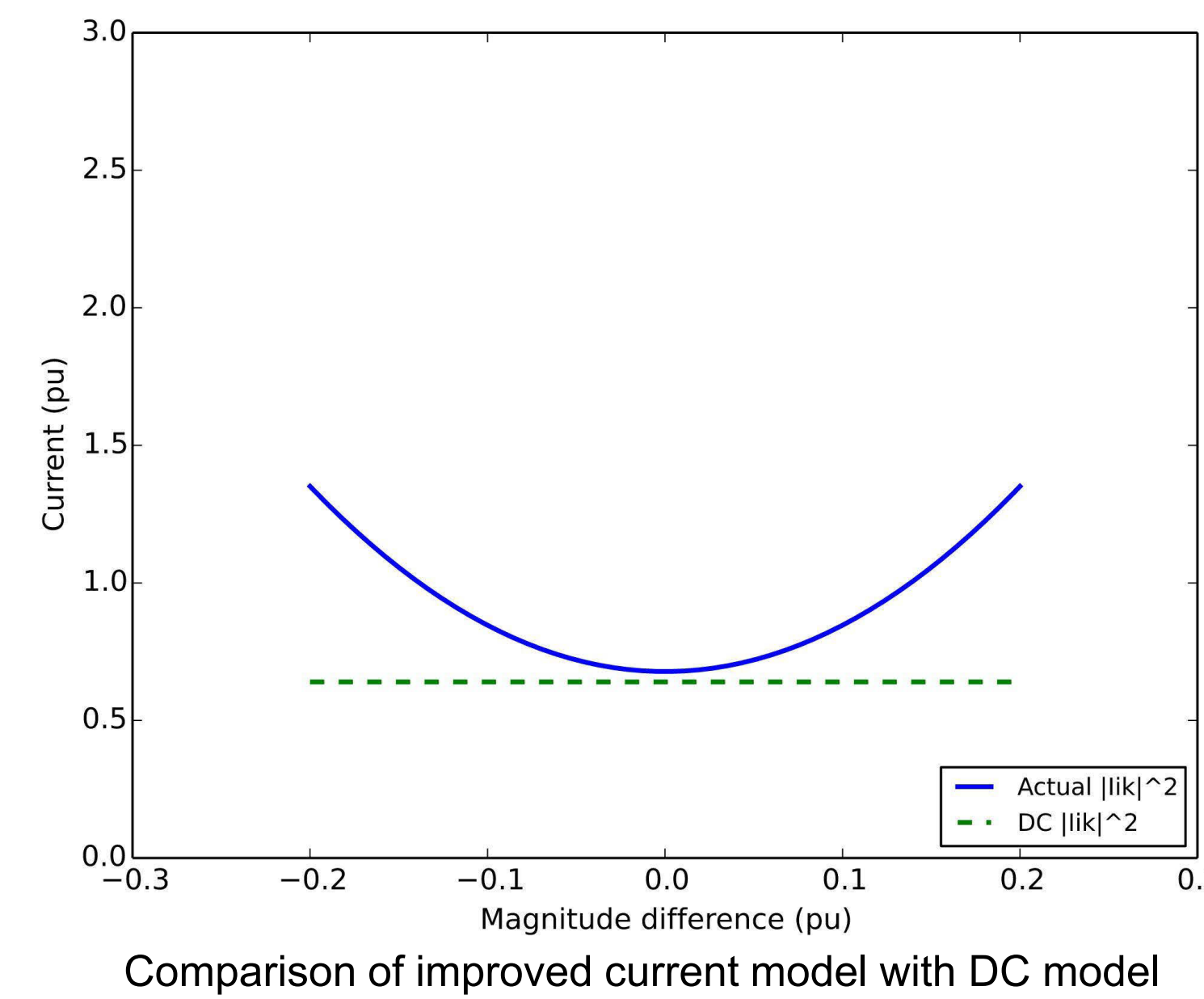


Two-dimensional depiction of instanton search. Starting from the forecast (dot), the dashed line shows the most likely shift in generation that would violate a constraint (solid line).

New Method: Current Constraint

Convexified network constraints form a tractable polytope.

Network constraints form a high-order polytope. Because this object may be expressed in terms of renewable generation, our optimization scheme can minimize over each face separately to obtain a ranked list of extreme events.



Constrained optimization formalizes the instanton problem.

By definition, the instanton is the most likely renewable generation pattern that violates one or more network constraints. To find the instanton candidate for a single constraint, we minimize deviation from forecast while saturating that constraint.

$$\min \frac{1}{2} (\mathbf{Q}_R - \mathbf{Q}_R^0)^\top \Lambda (\mathbf{Q}_R - \mathbf{Q}_R^0)$$

subject to network constraints and saturated constraint

Previous analysis uses DC power flow assumptions: 1) no line resistance, 2) small angle differences, 3) flat voltage profile, 4) no reactive power flows. Retain first two assumptions, drop last two.

Approximate expressions for real and imaginary current:

$$\begin{aligned} \text{Re}(I_{ik}) &\approx -B_{ik} [\text{Im}(E_i) - \text{Im}(E_k)] \\ \text{Im}(I_{ik}) &\approx B_{ik} [\text{Re}(E_i) - \text{Re}(E_k)] \end{aligned}$$

Square each term to obtain approximate current magnitude:

$$|I_{ik}|^2 \approx B_{ik} (V_i^2 + V_k^2 - 2V_i V_k \cos \theta_{ik})$$

Solve for angle:

$$\theta_{ik} = \cos^{-1} \left(\frac{V_i^2 + V_k^2 - (|I_{ik}^{\text{lim}}| x_{ik})^2}{2V_i V_k} \right)$$

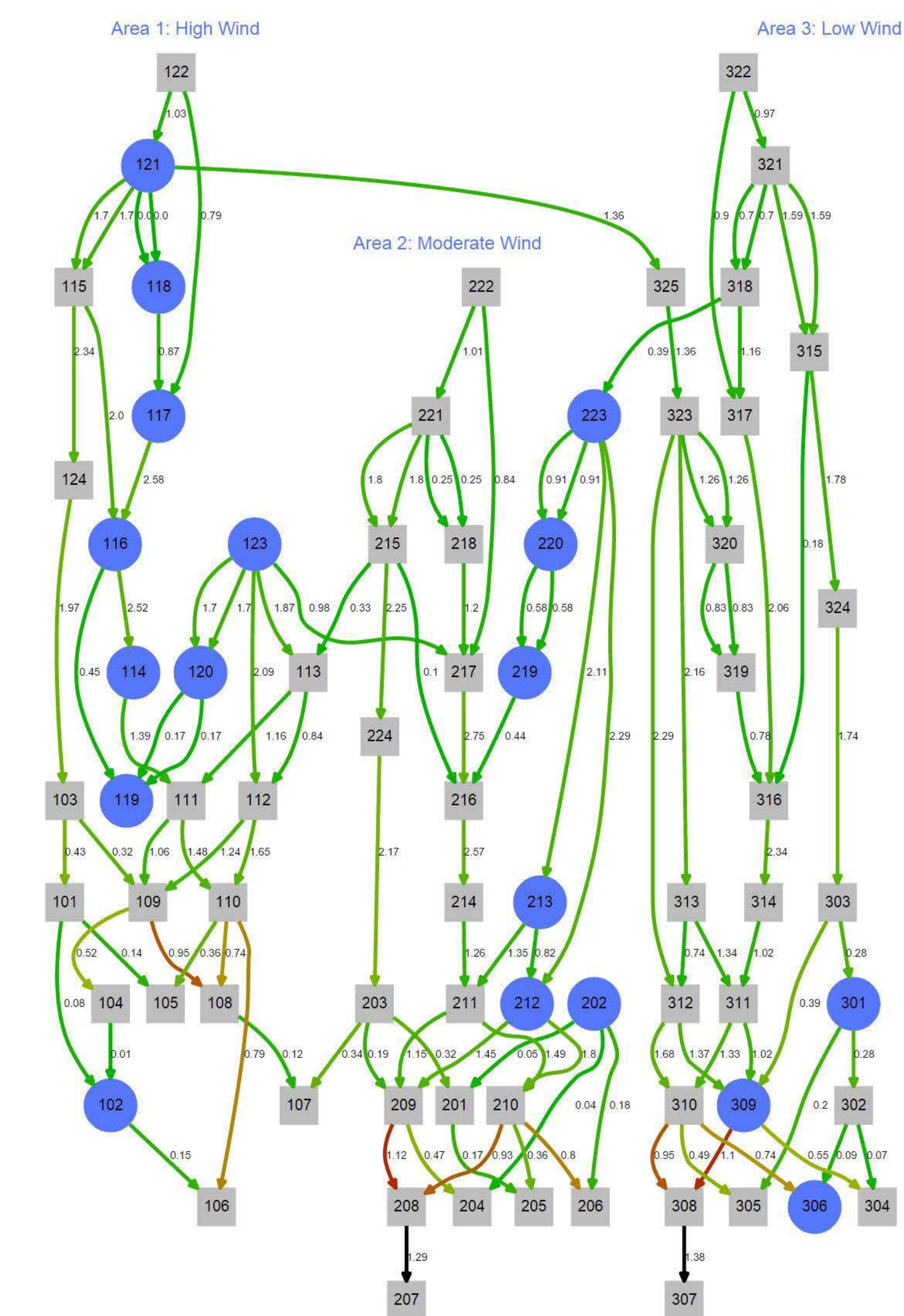
Compare with DC constraint: $\theta_{ik} = x_{ik} p_{ik}^{\text{lim}}$

Any line with significant voltage difference is more vulnerable than DC instanton analysis says.

PQ decoupling means we can pre-compute voltage magnitudes from reactive injections. (If voltages were not fixed, we would need to approximate cosine.)

Acknowledgements

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Stochastic Modeling and Simulations of Thermostatically Controlled Loads

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Abstract

We study a stochastic model of an ensemble of Thermostatically Controlled Loads. The study includes direct Markov Chain simulations of the ensemble, validation of the results against the Fokker-Planck type of theory in the regimes amenable for analytics, and then numerical exploration of various non-equilibrium properties of the system in more challenging regimes, e.g. analyzing response to demand response perturbations of practical interest. This is an early report on the study aimed at designing new controls of the TCL ensembles.

Two states control modelling

In the two states control modeling the state of a customer is described by the inside temperature, denoted by T and a discrete variable j that attains values $j = 2$ and $j = 1$ for the device (air conditioner) being off and on, respectively. Each regime is given by the Langevin equation aforementioned:

$$\dot{T} = -\frac{1}{\tau}(T - T_j) + \xi(T, t),$$

where T_2 and T_1 are the outside temperature and the inside temperature for permanently working air conditioner. We set dead-bands by initiating the bounds of the comfort zone T_{down} and T_{up} . Achieving one of them we change over the conditioner program.

The system of Fokker-Planck equations, established for such a model:

$$\begin{cases} \frac{\partial \rho_1}{\partial t} = \frac{D}{2} \frac{\partial^2 \rho_1}{\partial T^2} - \frac{\partial}{\partial T} (f_1(T) \rho_1) - r_{21}(T) \rho_2 + r_{12}(T) \rho_1 \\ \frac{\partial \rho_2}{\partial t} = \frac{D}{2} \frac{\partial^2 \rho_2}{\partial T^2} - \frac{\partial}{\partial T} (f_2(T) \rho_2) - r_{12}(T) \rho_1 + r_{21}(T) \rho_2 \end{cases},$$

$$\text{where } \begin{cases} f_j = -\frac{1}{\tau}(T - T_j) \\ r_{12}(T) = r \cdot \theta(T - T_{up}) \\ r_{21}(T) = r \cdot \theta(T - T_{down}) \end{cases}$$

We use $r \rightarrow \infty$ limit, because it is a correct way to describe the situation of instantaneous switching, once out of range.

The simplest model without control

The simplest model describes a behavior of a large number N of identical customers under the effect of the ambient. The state of a customer is characterized by the temperature, denoted by T . Stochastic dynamics for the temperature relaxation process is given by the Langevin equation:

$$\dot{T} = -\frac{1}{\tau}(T - T_{out}) + \xi(T, t), \text{ where the Gaussian noise } \xi(T, t) \text{ is assumed be } \begin{cases} \langle \xi(t) \rangle = 0 \\ \langle \xi(t_1) \xi(t_2) \rangle = D \cdot \delta(t_1 - t_2) \end{cases}$$

The Fokker-Planck equation, established for such a system:

$$\begin{cases} \dot{\rho} = \frac{1}{\tau} \partial_T [(T - T_{out}) \rho] + \frac{D}{2} \partial_T^2 \rho \\ \rho(T, 0) = \delta(T - T_0) \end{cases}$$

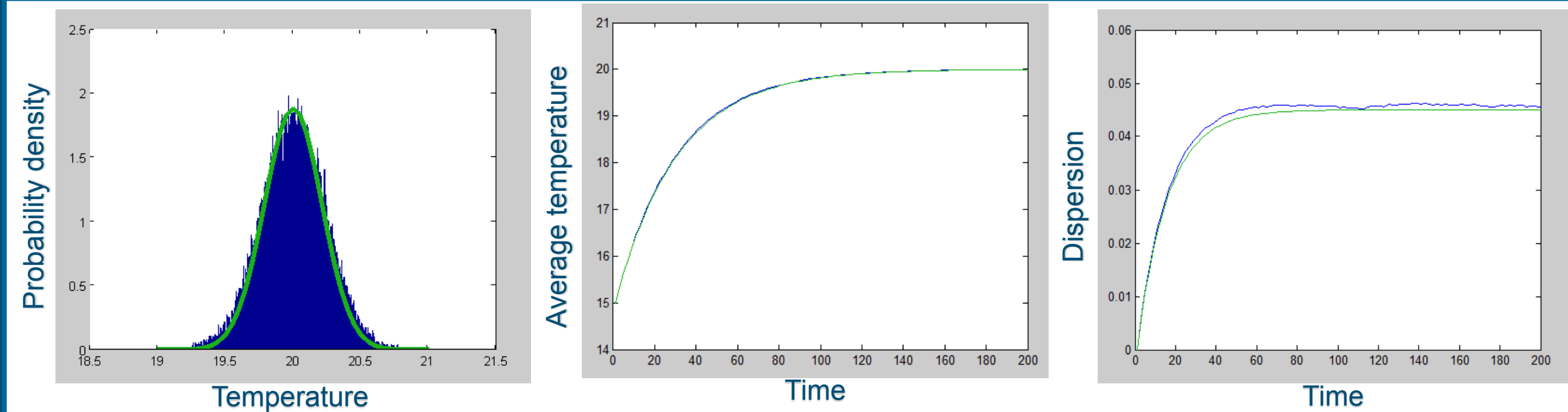
The solution:

$$\rho(T, t) = \frac{1}{\sqrt{\pi D \tau}} \cdot \frac{1}{\sqrt{1 - e^{-2t/\tau}}} \cdot \exp \left(-\frac{(T - T_{out}) + (T_{out} - T_0) e^{-t/\tau}}{D \tau (1 - e^{-2t/\tau})} \right)^2.$$

The simple iteration method in application to the Langevin equation:

$$T_{i+1} = T_i - \frac{dt}{\tau} (T_i - T_{out}) + \xi \sqrt{dt}.$$

Results of the simplest model simulations



The stationary temperature distribution

The average temperature dependence on time.

The dispersion dependence on time.

Green line – solution to the Fokker-Planck equation

Blue line – simulation result
Green line – theoretically established function

$$T_{average}(t) = T_{out} - (T_{out} - T_0) e^{-t/\tau}$$

Blue line – simulation result
Green line – theoretically established function

$$\sigma(t) = \frac{D\tau}{2} (1 - e^{-2t/\tau})$$

Simulation parameters

$N = 50\,000$

$Mtime = 1000$ ($dt = 0.01$)

$D = 0.3$

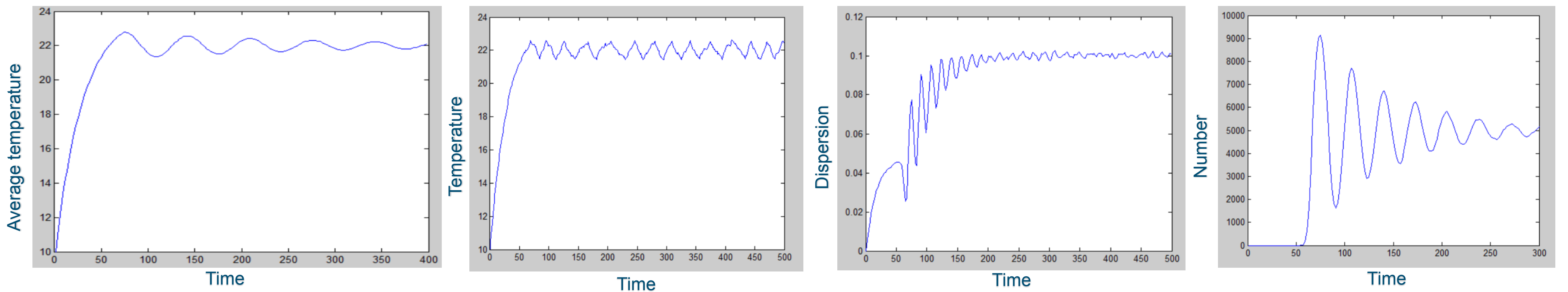
$\tau = 0.3$

$T_{out} = 20^\circ C$

$T_0 = 15^\circ C$

A range of parameters, such as D , τ , T_{out} , N and $Mtime$, effect the temperature relaxation process. The more D or τ are, the wider the temperature distribution is and the more the stationary dispersion value is. The less dt is, the closer to reality we are, but the more time steps we have to do to achieve the stationarity so the more the time of calculations is. The diminution between T_{out} and T_0 influences the relaxation time.

Results of the two states control model simulations



The average temperature dependence on time.

The temperature of a random customer on time.

The dispersion dependence on time.

The number of ON-state customers on time.

Perturbations are quite high at the beginning, but they are decreasing in time.

Because of control the customers go back and forth between dead-bands passing round.

While all customers are switched off/on, the dispersion is as the same as in the simplest case without control. Perturbations of the dispersion are decreasing in time quite slowly.

Because of noise perturbations are decreasing in time and approaching to $N/2$. If we set, for example, heating force bigger than the freezing one, the stationary number will be bigger.

Simulation parameters

$N = 100\,000$

$Mtime = 1000$

$dt = 0.01$

$D = 0.3$

$\tau = 0.3$

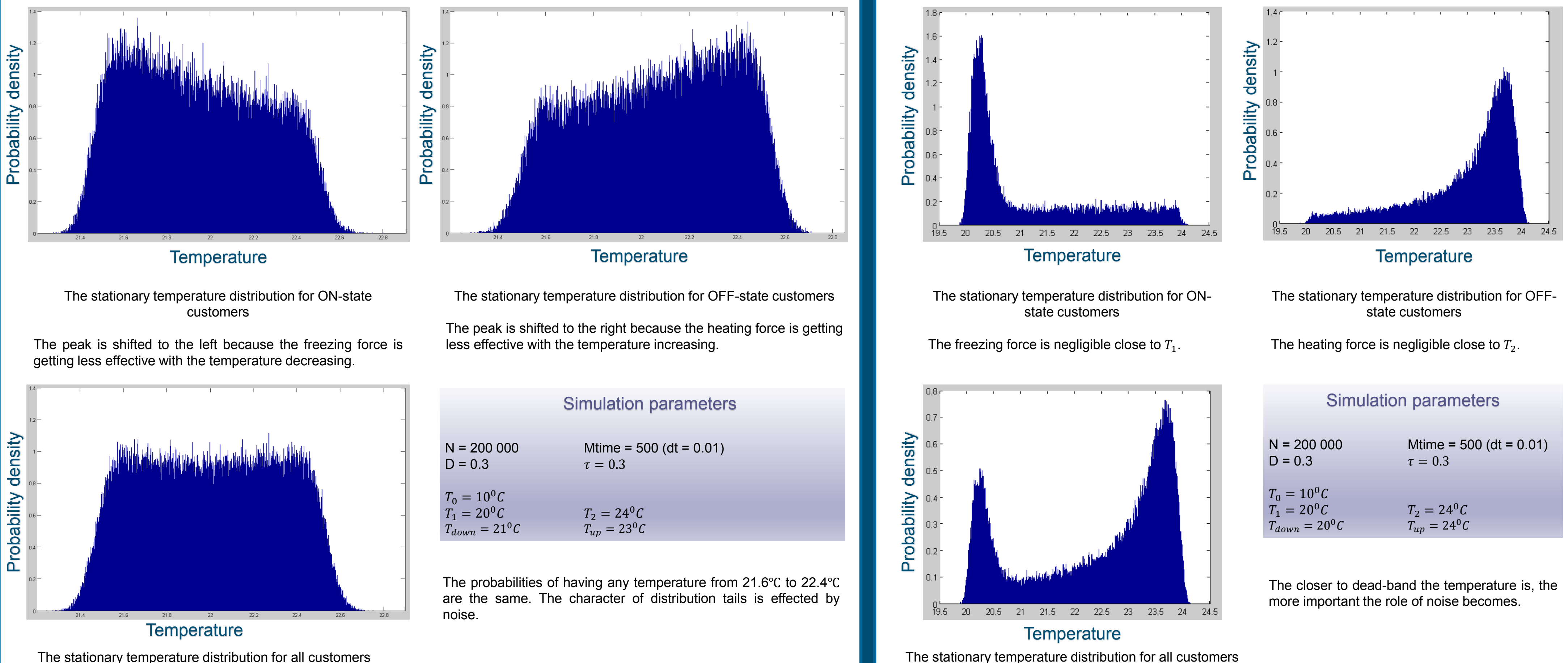
$T_0 = 10^\circ C$

$T_1 = 20^\circ C$

$T_2 = 24^\circ C$

$T_{down} = 21^\circ C$

$T_{up} = 23^\circ C$



The stationary temperature distribution for ON-state customers

The stationary temperature distribution for OFF-state customers

The peak is shifted to the left because the freezing force is getting less effective with the temperature decreasing.

The peak is shifted to the right because the heating force is getting less effective with the temperature increasing.

The stationary temperature distribution for ON-state customers

The stationary temperature distribution for OFF-state customers

The freezing force is negligible close to T_1 .

The heating force is negligible close to T_2 .

Simulation parameters

$N = 200\,000$

$Mtime = 500$ ($dt = 0.01$)

$\tau = 0.3$

$T_0 = 10^\circ C$

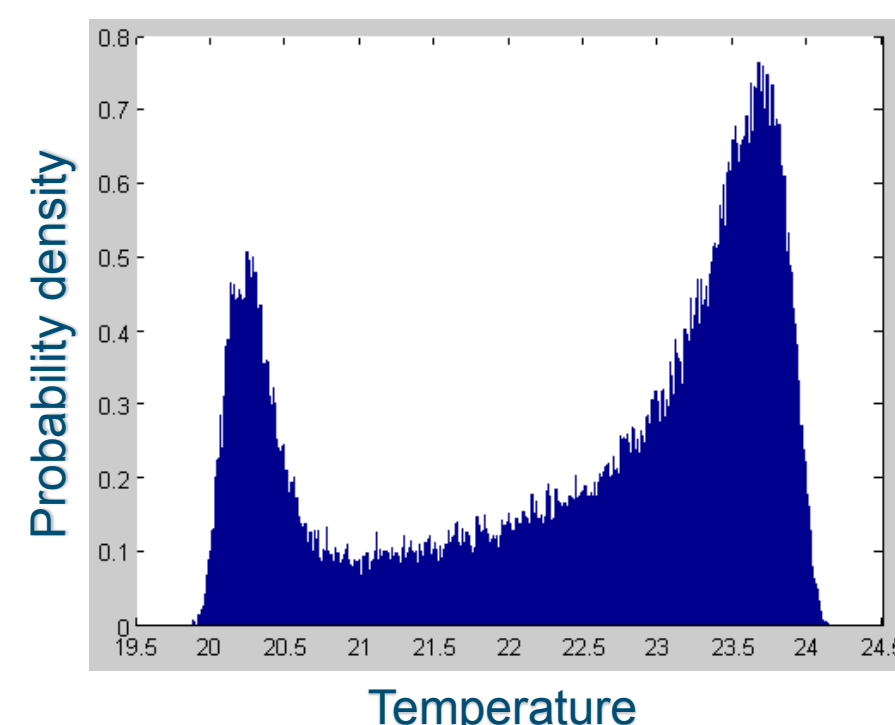
$T_1 = 20^\circ C$

$T_{down} = 21^\circ C$

$T_2 = 24^\circ C$

$T_{up} = 23^\circ C$

The probabilities of having any temperature from $21.6^\circ C$ to $22.4^\circ C$ are the same. The character of distribution tails is effected by noise.



The stationary temperature distribution for all customers

Simulation parameters

$N = 200\,000$

$Mtime = 500$ ($dt = 0.01$)

$\tau = 0.3$

$T_0 = 10^\circ C$

$T_1 = 20^\circ C$

$T_{down} = 20^\circ C$

$T_2 = 24^\circ C$

$T_{up} = 24^\circ C$

The closer to dead-band the temperature is, the more important the role of noise becomes.

Conclusion and plans for future

We have researched some system properties concerning to stationary temperature distributions and some time-variable characteristics in different regimes. These results are preliminary. In the nearest future we are planning to validate our results theoretically. The system behavior researching brings us to creation of an algorithm of demand-response control.

On Reactive Power Flow and Voltage Stability in Microgrids

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ABSTRACT

As of today, solutions to the reactive power flow can be found only via numerical methods, yet an analytical understanding would be beneficial to the rigorous design of future electric grids. Firstly, for sufficiently high reference voltages, we guarantee the existence of a high-voltage solution for the reactive power flow and provide its approximate analytical expression (RDC approximation). We validate the accuracy of our approximation through numerical simulation of the IEEE 37 test case. Secondly, we consider a recently proposed droop control for voltage stabilization in a microgrid equipped with inverters. We prove the existence and the exponential stability of a high-voltage fixed point of the closed-loop dynamics. We provide an approximate expression for this fixed point.

TWO-NODE GRID

Figure 1 shows a grid composed by a source (or PV bus) and a load (or PQ bus), connected by a power line. The reactive power flow at the load reads

$$Q_L = V_L^2 \ell - V_L V_S \cos(\theta_L - \theta_S) \ell - V_L V_S \sin(\theta_L - \theta_S) g \simeq V_L^2 \ell - V_L V_S \ell. \quad (1)$$

The last approximation derives from the fact that during regular power system operation the angles difference is negligible.

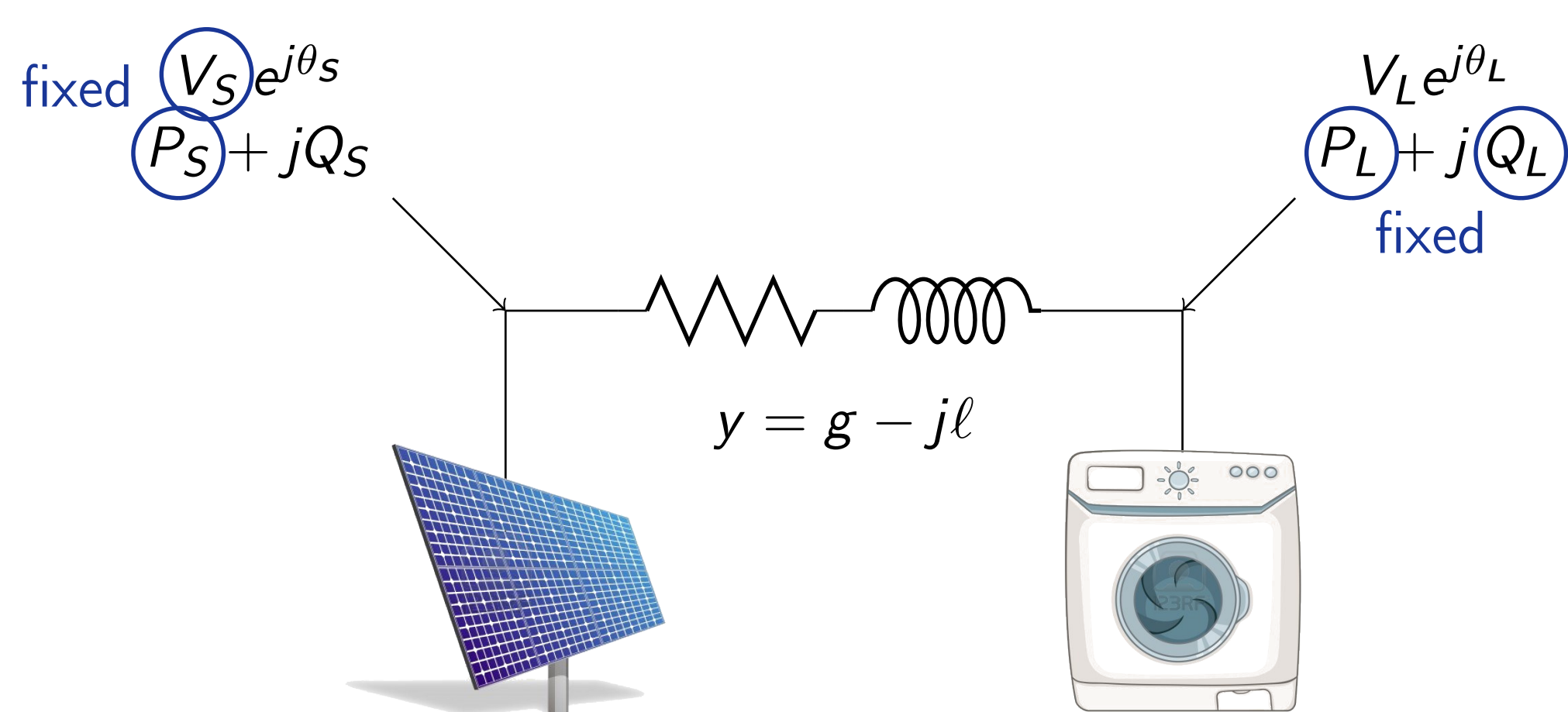


Figure 1: two-node grid

In the two-node case (1) becomes a second order equation with solution

$$V_{L,1,2} = V_S \left(\frac{1}{2} \pm \frac{1}{2} \sqrt{1 + \frac{4Q_L}{\ell V_S^2}} \right) \quad \text{if } V_S \geq \sqrt{-\frac{4Q_L}{\ell}}.$$

If $4Q_L/(\ell V_S^2) \ll 1$ the first-order Taylor expansion of the square root yields

$$V_{L,1} \simeq V_S + \frac{Q_L}{\ell V_S}, \quad V_{L,2} \simeq -\frac{Q_L}{\ell V_S}.$$

The solution $V_{L,1}$ is the desired one, as it corresponds to a high-voltage low-current configuration for the network, resulting in low power losses. We can interpret the solution as being an odd-exponent power expansion in the source voltage V_S , with the first term neglected being of the order of $1/V_S^3$.

RDC APPROXIMATION

In order to generalize the concepts introduced with the two-node grid, we model a power network in synchronous steady-state as a connected graph (see Figure 2). The nodes of the graph are partitioned into sources (or PV buses, red circles in Figure 2) and loads (or PQ buses, blue squares in Figure 2); the edges represent the power lines.

By applying the same decoupling assumption introduced for the two-node case, the reactive power flow reads

$$Q_L = \text{diag}(V_L) [L_{LL} \quad L_{LS}] \begin{bmatrix} V_L \\ V_S \end{bmatrix}. \quad (2)$$

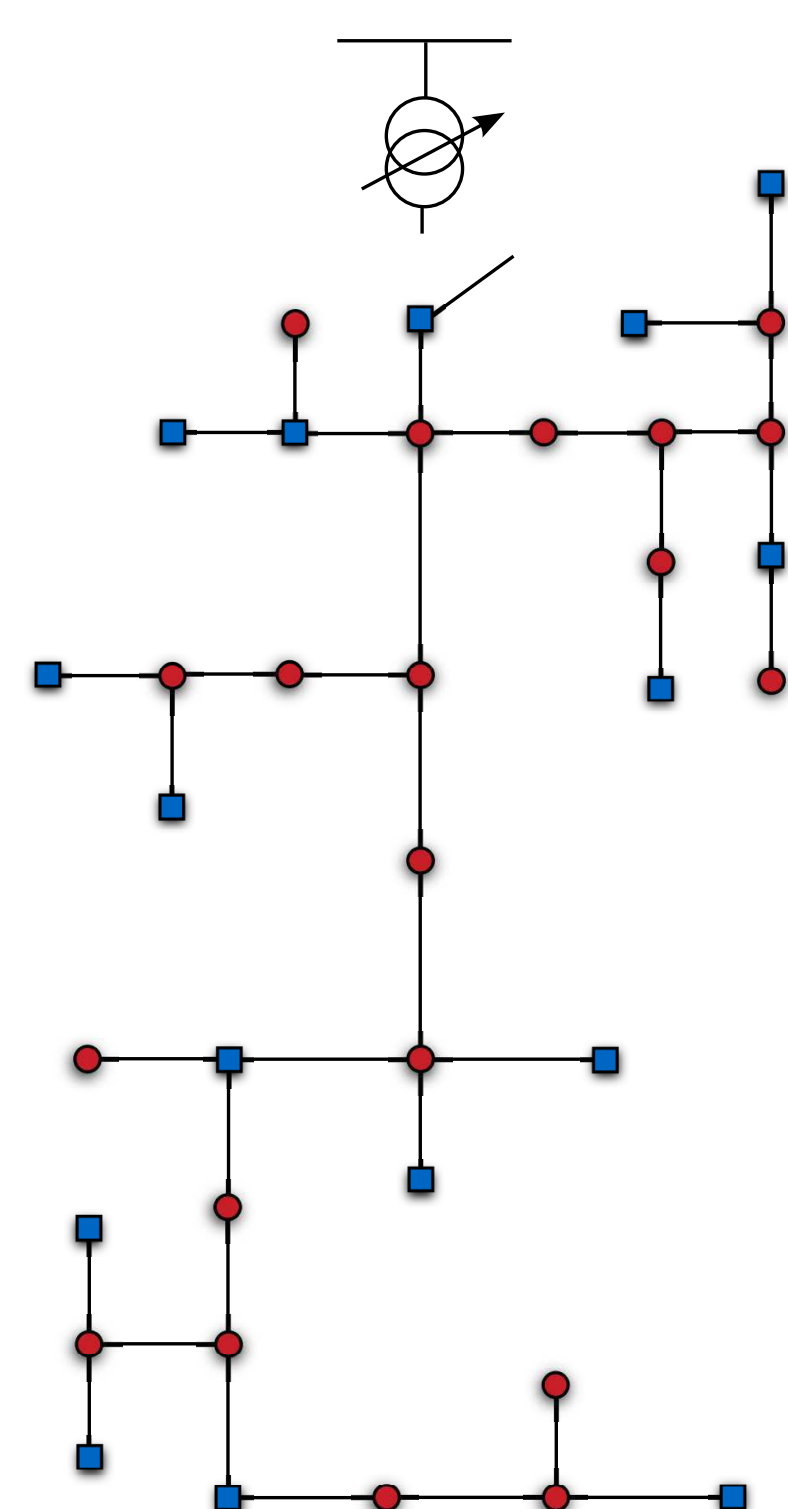
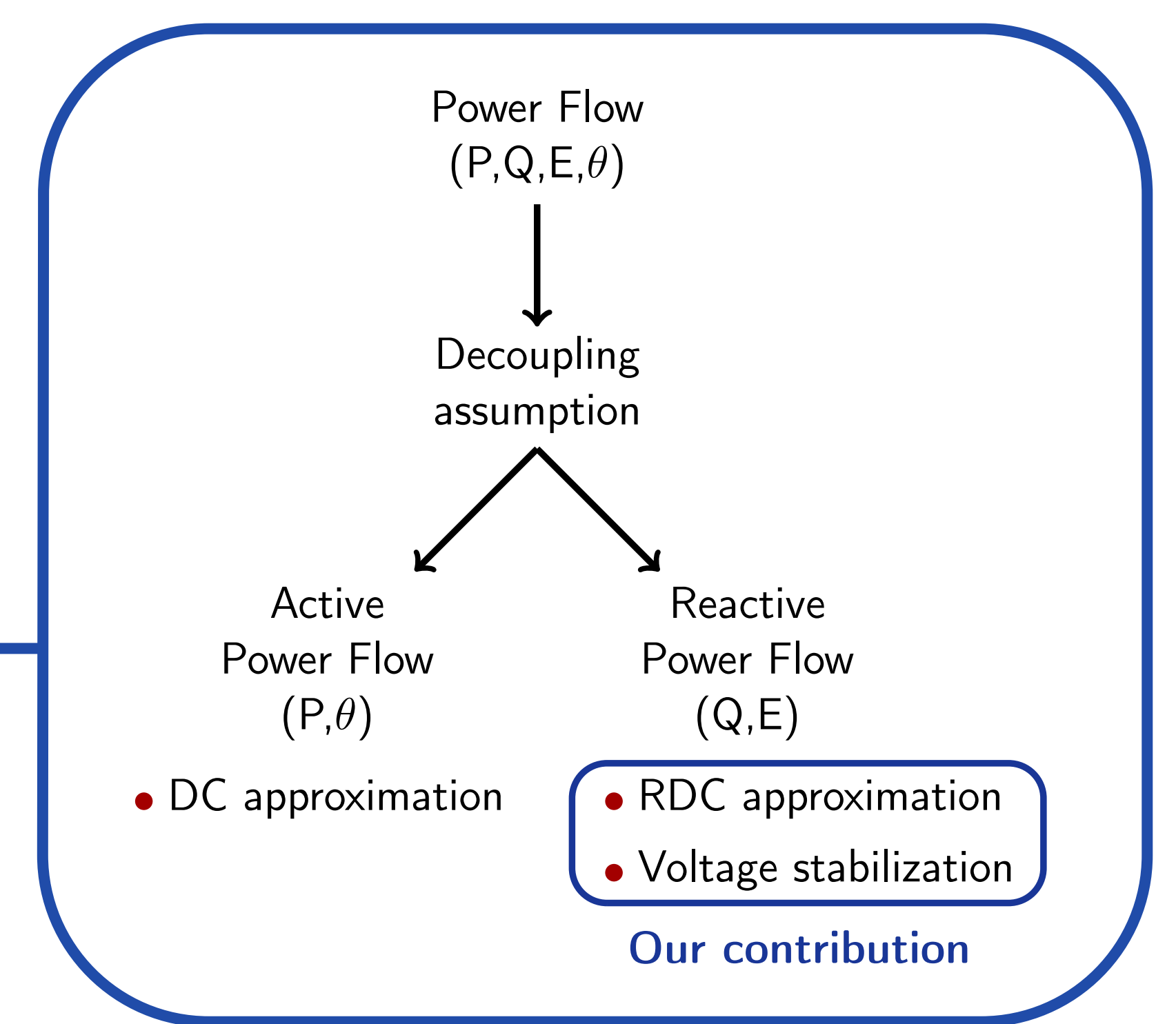


Figure 2: IEEE 37 grid



It is not possible to derive an explicit analytic solution for the system (2) of quadratic equations in the variables V_L , yet the practical importance of the reactive power flow motivates the interest in extending the results of the two-node case to the system (2). To this end the preliminary concepts of source baseline voltage V_N and source voltage spread η must be introduced:

$$V_N := \min_i \{V_i, i \in S\} \quad \eta : V_S = (1 + \eta) V_N.$$

Theorem (RDC approximation).

If $E_N > \sqrt{\frac{4\|L_{LL}^{-1}\| \cdot \|Q_L\|}{\min_i \{1 + (L_{LL}^{-1} L_{LS} \eta)_i\}^2}}$ the reactive power flow admits the solution

$$V_L = V_L^{RDC} + \mathcal{O}\left(\frac{1}{V_N^3}\right)$$

$$\text{where } V_L^{RDC} := V_N (1 - L_{LL}^{-1} L_{LS} \eta) + \frac{1}{V_N} (L_{LL}^{-1} \text{diag}^{-1} (1 - L_{LL}^{-1} L_{LS} \eta) Q_L).$$

It is worth noticing that the threshold above which the existence of a solution is guaranteed is a generalization of the threshold found for the two-node grid; in the same way, the RDC approximation V_L^{RDC} generalizes the Taylor-expansion proposed in the two-node case.

NUMERICAL ACCURACY

We studied the IEEE 37 test case (Figure 2) and compared the RDC approximation to the numerical solution of the system (2), for different values of the baseline voltage V_N . Figure 3 reports the relative approximation error: we can notice that at the network operating voltage of 4.8 kV the relative error is of the order of 10^{-6} .

Moreover, one can measure from the plot that the approximation error tends to zero as $1/V_N^3$, as predicted by the above Theorem.

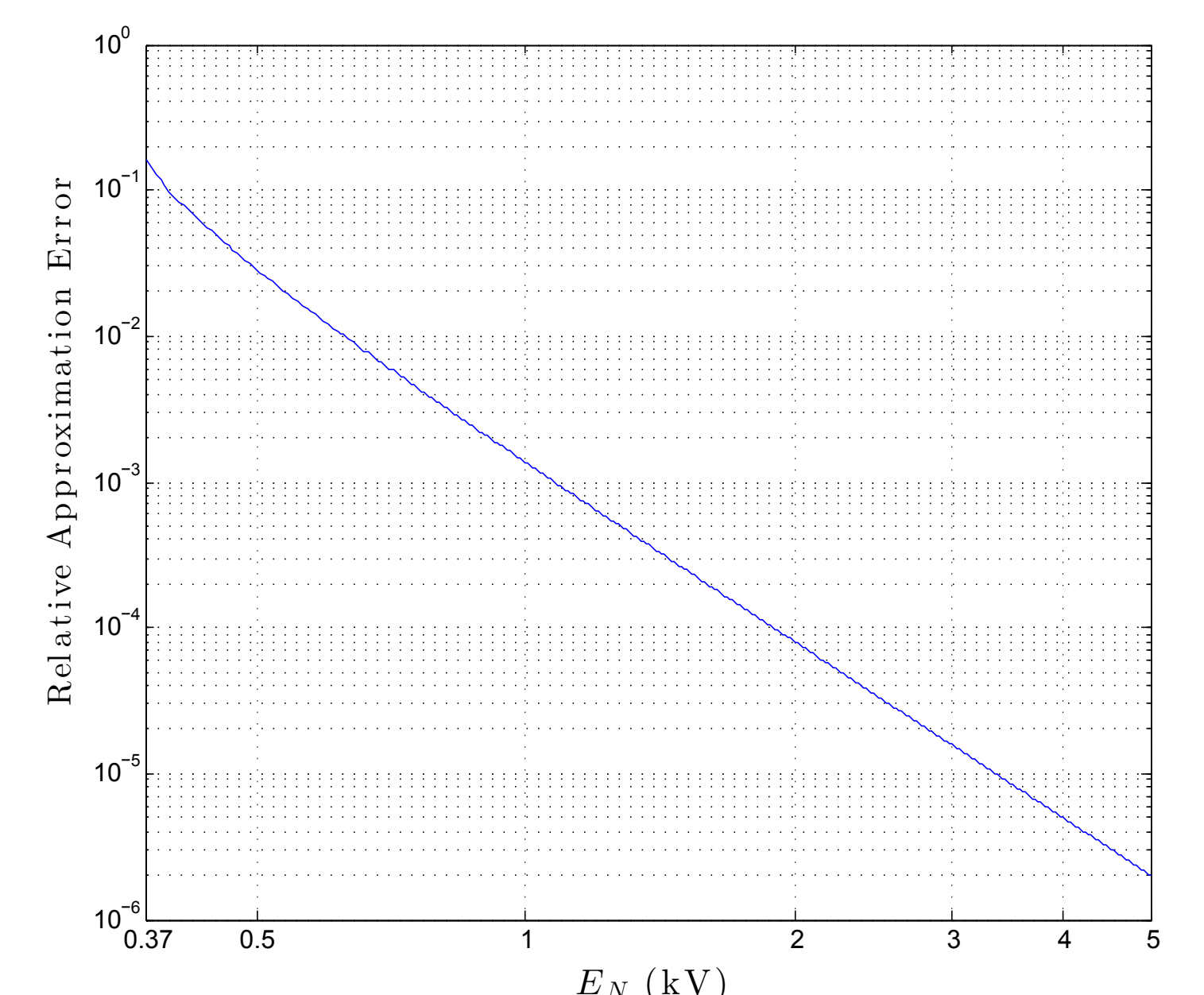


Figure 3: the relative approximation error

APPLICATION TO DROOP CONTROL

The RDC approximation can be used to study the problem of voltage stabilization in an inverter-based microgrid. The sources of the grid represent inverters which are regulated by [2]:

$$\dot{V}_i = -C_i V_i (V_i - V_i^R) - Q_i, \quad i \in S,$$

where V_i^R is the reference voltage for inverter i and C_i is a fixed parameter. Coupling this control law with the reactive power flow (1) yields

$$\begin{bmatrix} 0 \\ \dot{V}_S \end{bmatrix} = \begin{bmatrix} Q_L \\ C \text{diag}(V_S) (V_R - V_S) \end{bmatrix} - \text{diag}(V) L V.$$

By using the RDC approximation it is possible to show that such differential-algebraic system possesses a high-voltage locally exponentially stable fixed point and to provide an approximate expression of the fixed point.

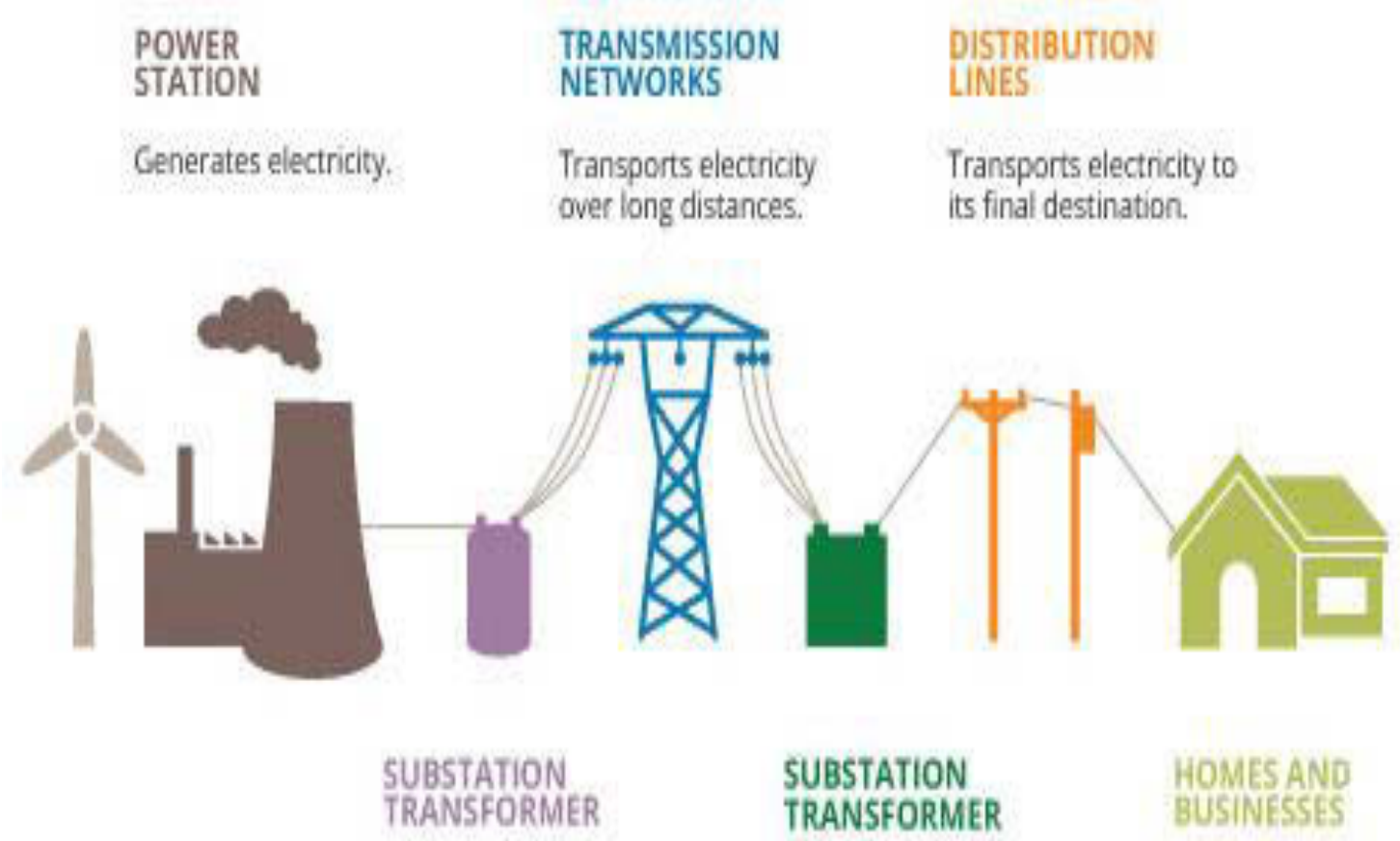
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Structure Learning and Statistical Estimation in Radial Distribution Networks

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MOTIVATION

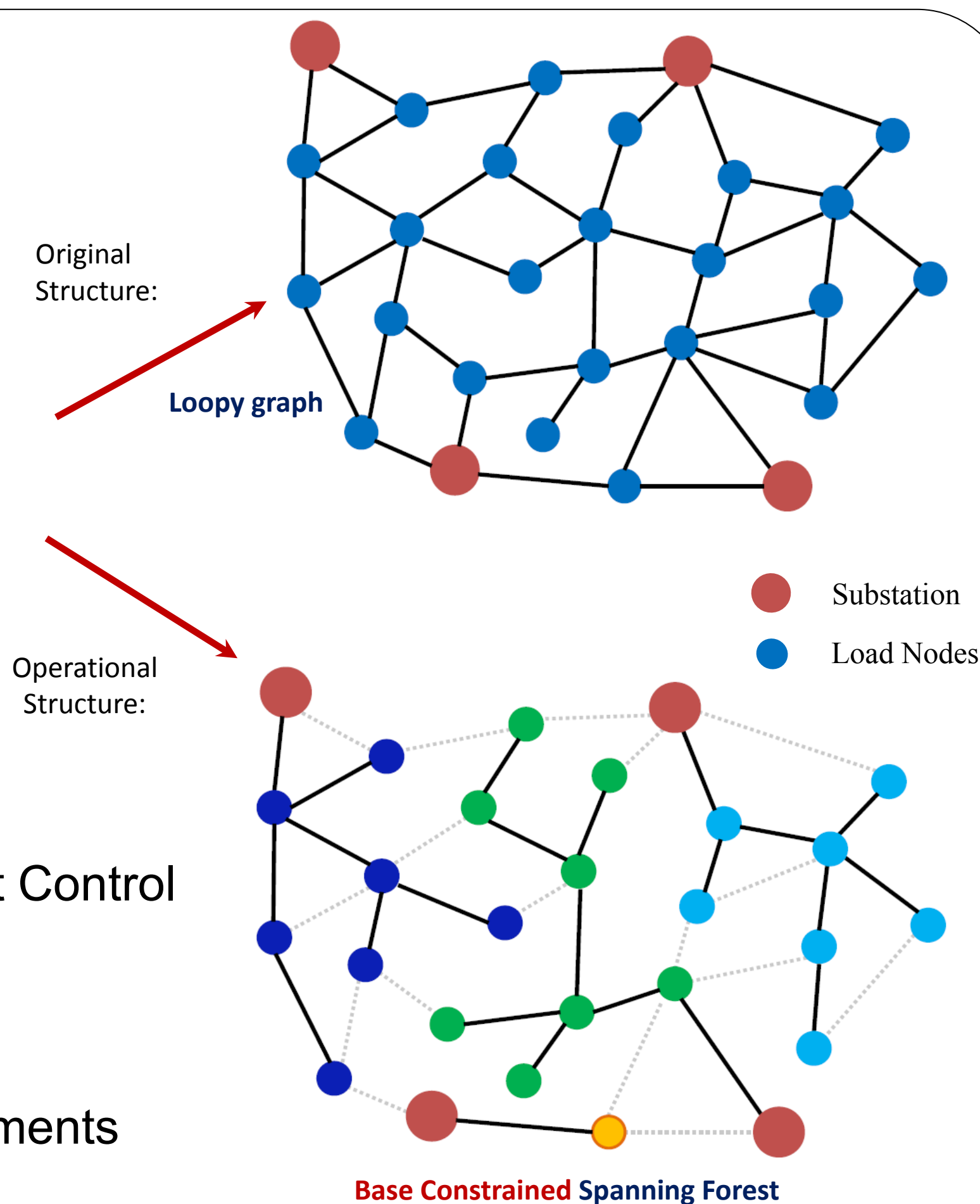


Distribution Grid

- Final tier in electricity transfer
- Influences: Demand Response/ Smart Control
- Insufficient measurements

Data available: (No line data)

- Node voltage and/or phasor measurements



SYSTEM MODEL

AC power flow:

$$P_a + iQ_a = \sum_{(a,b) \text{ is edge}} \frac{\varepsilon_a e^{i\theta_a} (\varepsilon_a e^{-i\theta_a} - \varepsilon_b e^{-i\theta_b})}{(R_{ab} - iX_{ab})}$$

*** LC lossless power flow ***

$$V_a = \varepsilon_a - 1 \approx 0, \theta_a \approx 0$$

$$P = (M^T B M)\theta + (M^T G M)V = H_B \theta + H_G V$$

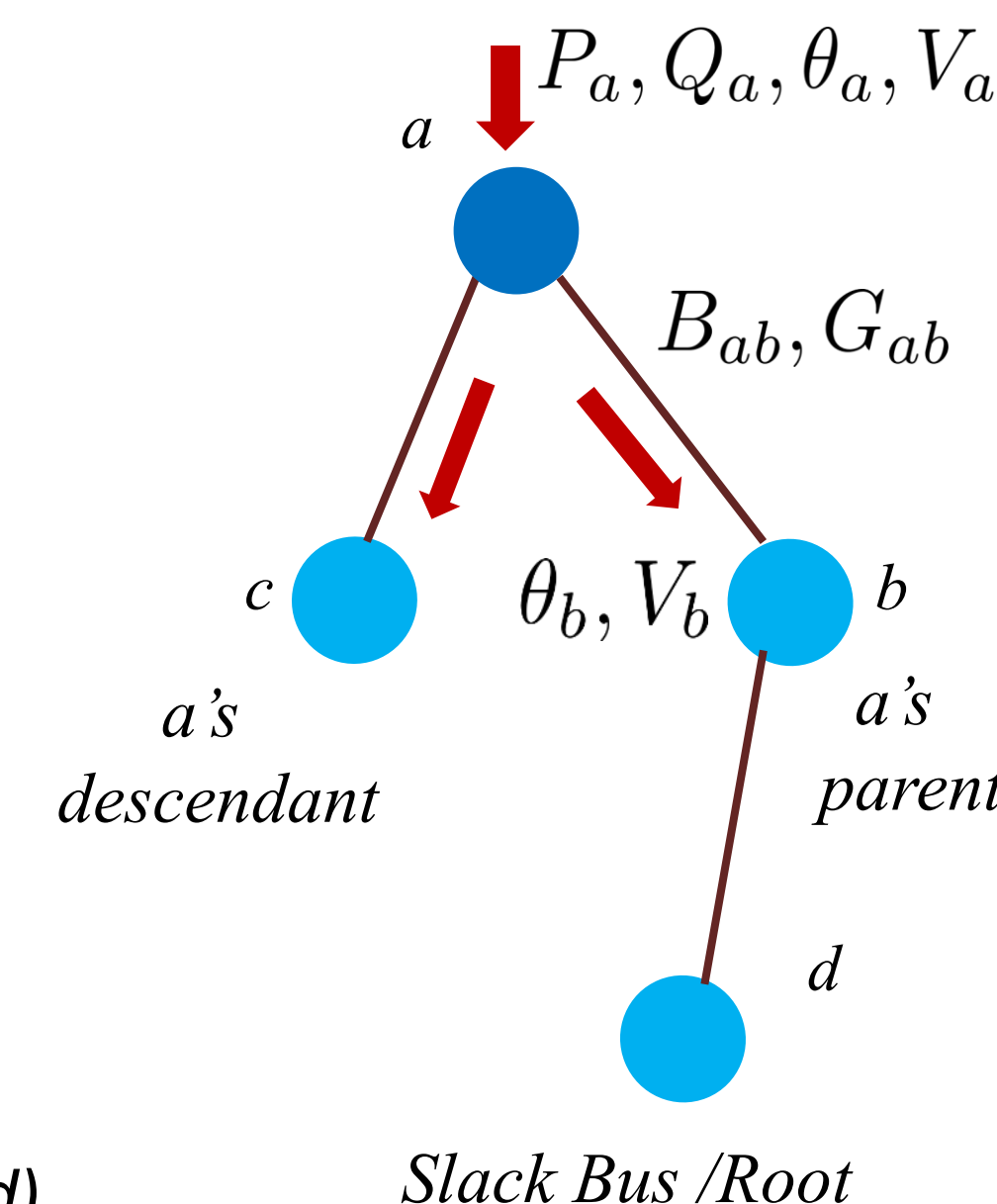
$$Q = -(M^T G M)\theta + (M^T B M)V = -H_G \theta + H_B V$$

$$\begin{aligned} \theta &= H_{1/X}^{-1} P - H_{1/R}^{-1} Q \\ V &= H_{1/R}^{-1} P + H_{1/X}^{-1} Q \end{aligned} \quad \left\{ \begin{array}{l} \text{Additive \& Separable (Good)} \\ \text{Has weighted Laplacians (Better)} \end{array} \right.$$

$$\Sigma_V = \mathbb{E}[V V^T]$$

➤ Second Moment

$$\Omega_V = \mathbb{E}[(V - \mu_V)(V - \mu_V)^T] \quad \text{➤ Covariance}$$



TREES ARE GOOD!!

$$M = \begin{pmatrix} 1 & -1 & 0 & 0 \\ 1 & 0 & -1 & 0 \\ 0 & 1 & 0 & -1 \end{pmatrix} \quad M^{-1} = \begin{pmatrix} 1 & 0 & 1 \\ 0 & 0 & 1 \\ 1 & -1 & 1 \end{pmatrix}$$

Reduced Incidence Matrix: **INVERSE IS 0 - 1**

$$H_B = \begin{pmatrix} B_{ab} + B_{ac} & -B_{ab} & -B_{ac} \\ -B_{ab} & B_{ab} + B_{bd} & -B_{bd} \\ -B_{ac} & 0 & B_{ac} \end{pmatrix} \quad \text{Reduced Weighted Laplacian Matrix}$$

$$H_B^{-1}(a, b) = \sum_{(i,j) \in E_a \cap E_b} \frac{1}{B_{ij}} \quad \text{TRACTABLE INVERSE}$$

sum of inverse susceptance of lines common to paths from a & b to slack bus

SUMMARY OF RESULTS

Considered Learning Problems:

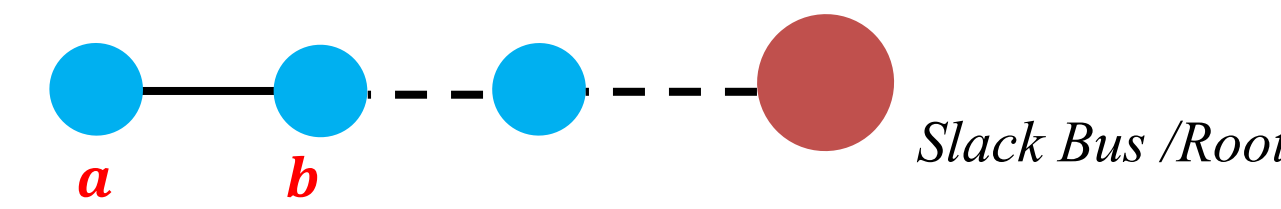
- Structure Learning:** current operational state
- Estimation of **Load Statistics** (mean/correlations)
- Learning with **Missing Data** (limited observations)

Potential Uses

- Failure detection
- Flow optimization
- Non-intrusive control
- Privacy quantification

STATISTICAL TRENDS IN TREES

- If node **b** is parent of node **a**,



- $\Sigma_V(a, a) > \Sigma_V(b, b)$
- $\Omega_V(a, a) > \Omega_V(b, b)$
- Highest second-moment at leaf node**

$$\begin{aligned} \mathbb{E}[(V_a - V_b)^2] &= \sum_{k_1, k_2 \in D_a^{\tau_i}} R_{ab}^2 \Sigma_P(k_1, k_2) \\ &\quad + 2R_{ab} X_{ab} \Sigma_{PQ}(k_1, k_2) + X_{ab}^2 \Sigma_Q(k_1, k_2) \end{aligned}$$

- Mean sq. difference contributed only by descendant nodes**

$$b = \arg \min_{k \notin D_a^{\tau_i}} \mathbb{E}[(V_a - \mu_{V_a}) - (V_k - \mu_{V_k})]^2$$

- Minimum mean sq. centered difference among non-descendants at parent**

STRUCTURE LEARNING ALGORITHMS

ASSUMPTIONS considered

$$\Sigma_P(a, b) > 0, \Sigma_Q(a, b) > 0, \Sigma_{PQ}(a, b) > 0$$

$$\Omega_{QP}(a, a) \geq 0$$

$$\Omega_P(a, b), \Omega_Q(a, b), \Omega_{QP}(a, b) = 0 \forall a \neq b$$

ALGORITHM:

- Pick undiscovered node **b** with largest Σ_V OR Ω_V
- For every discovered node **a**, join **b** with **a** if

** All load nodes are **energy consumers**

** Fluctuations at different nodes are **uncorrelated**, at same node are **aligned**

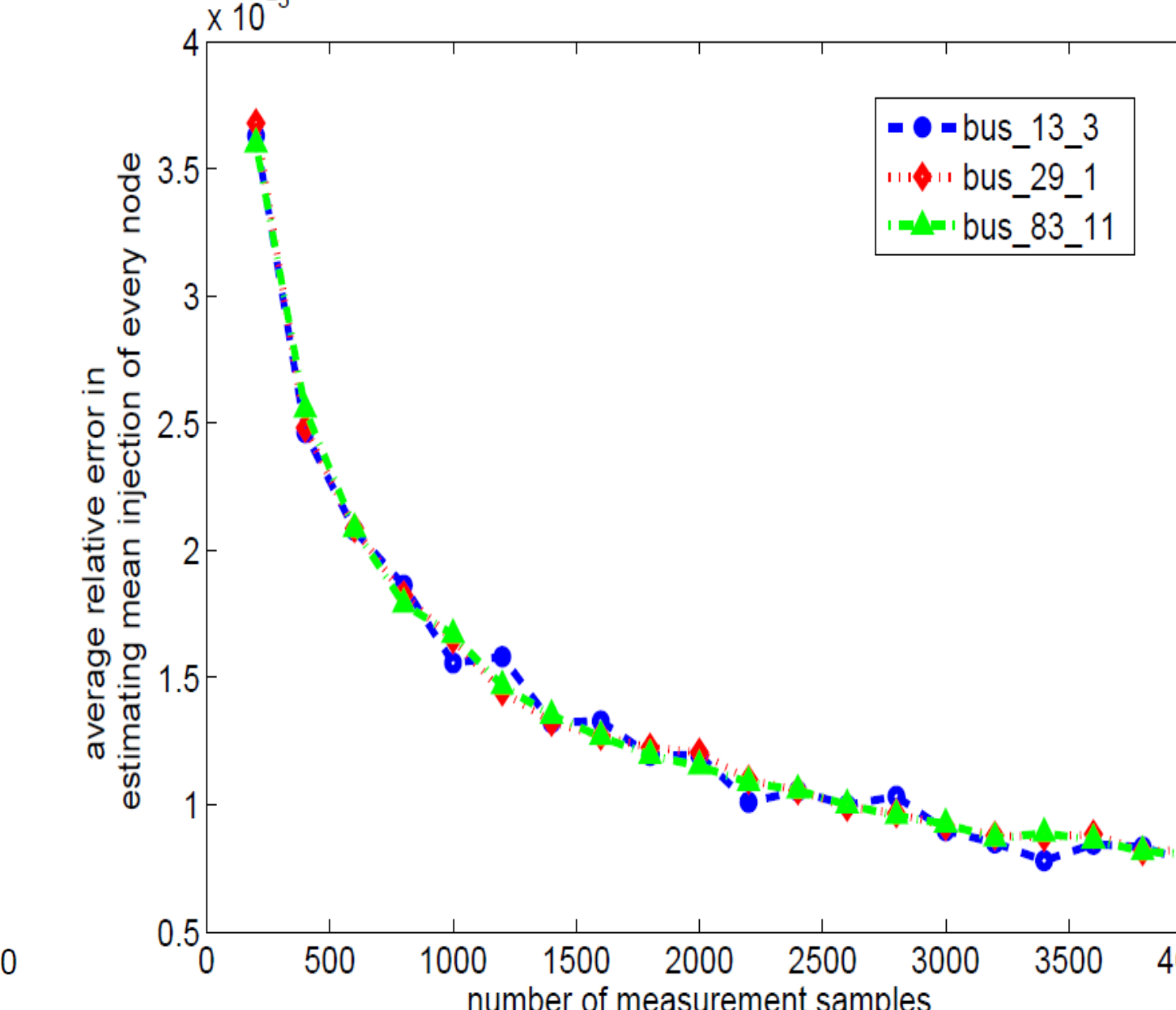
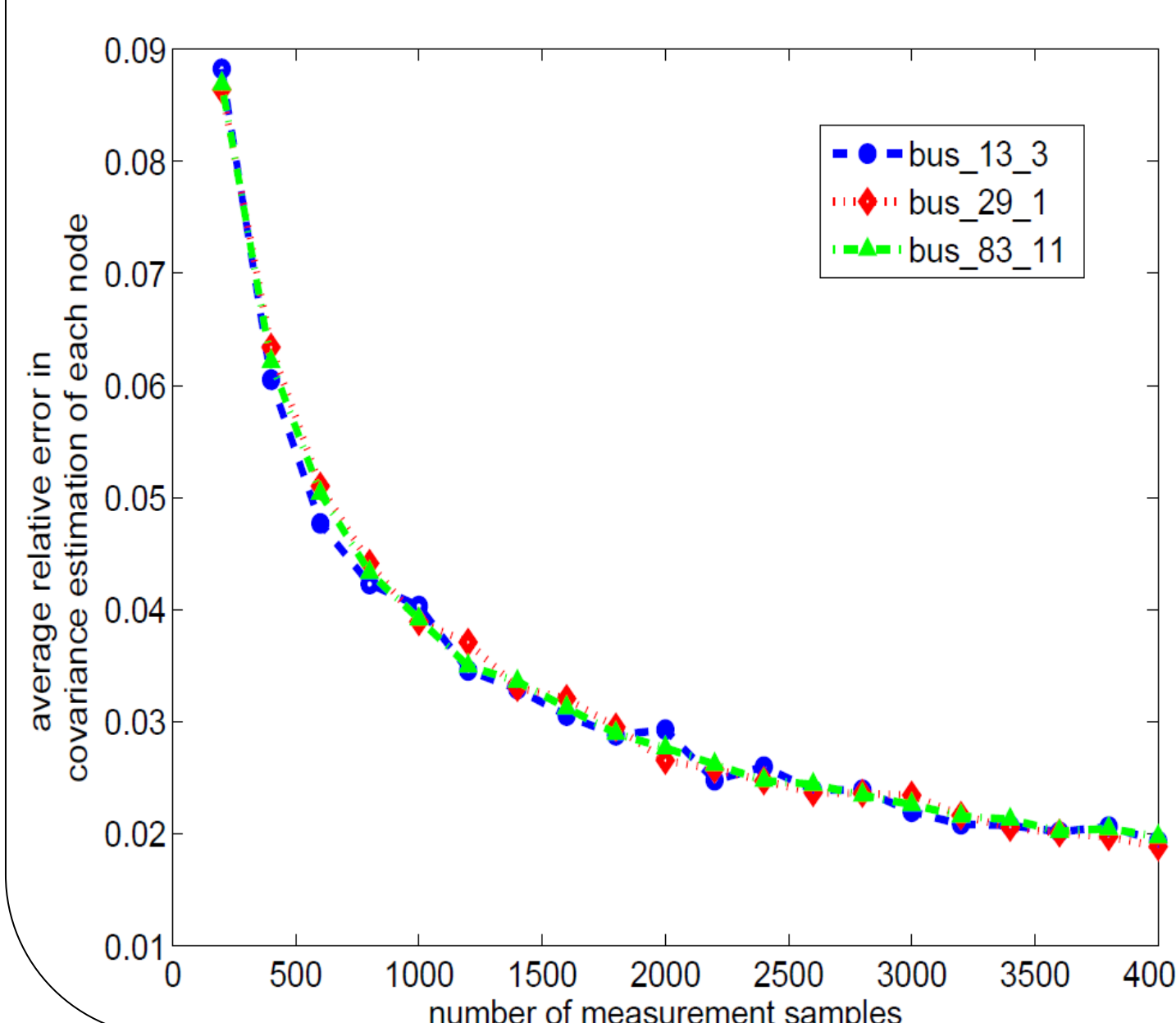
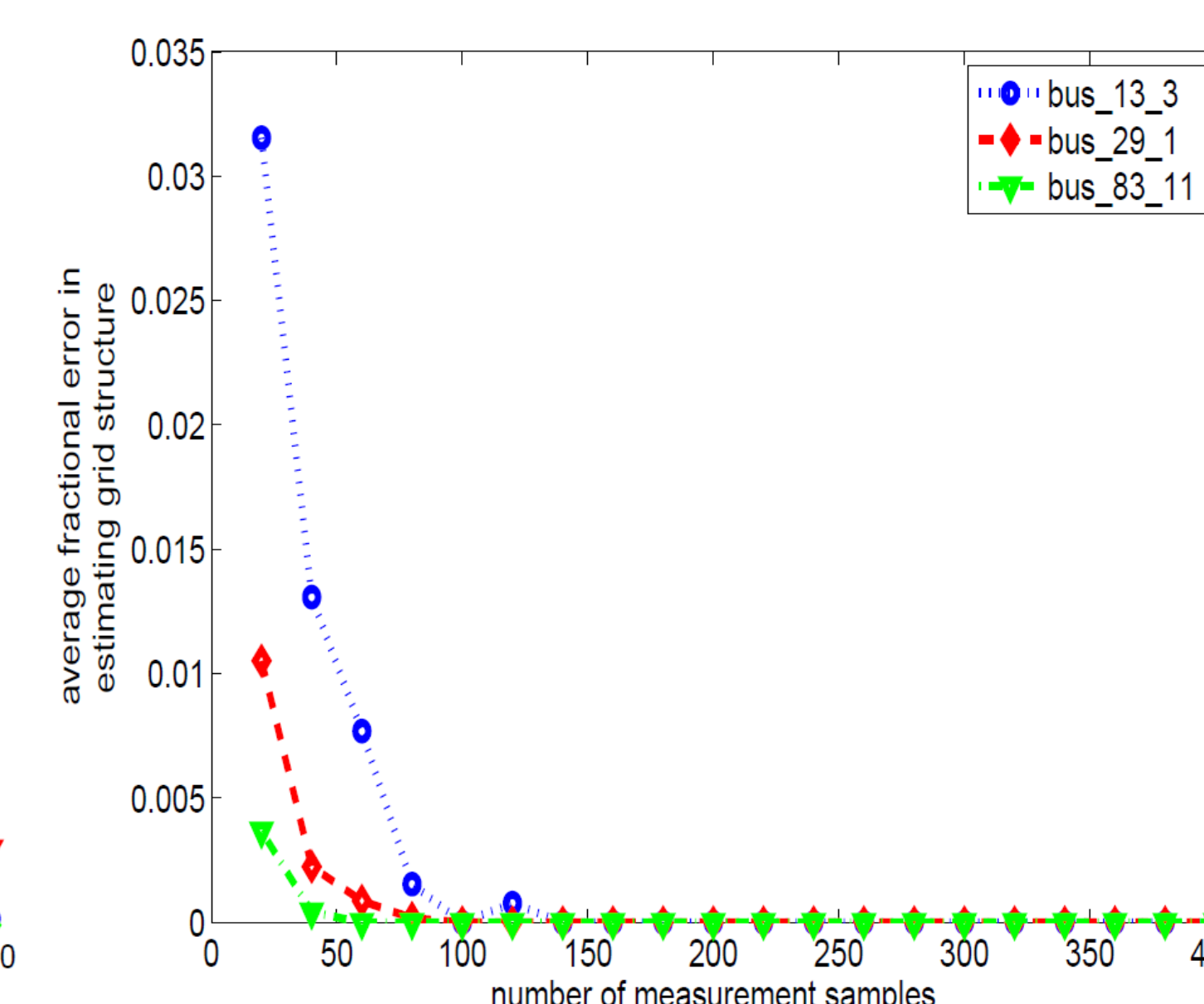
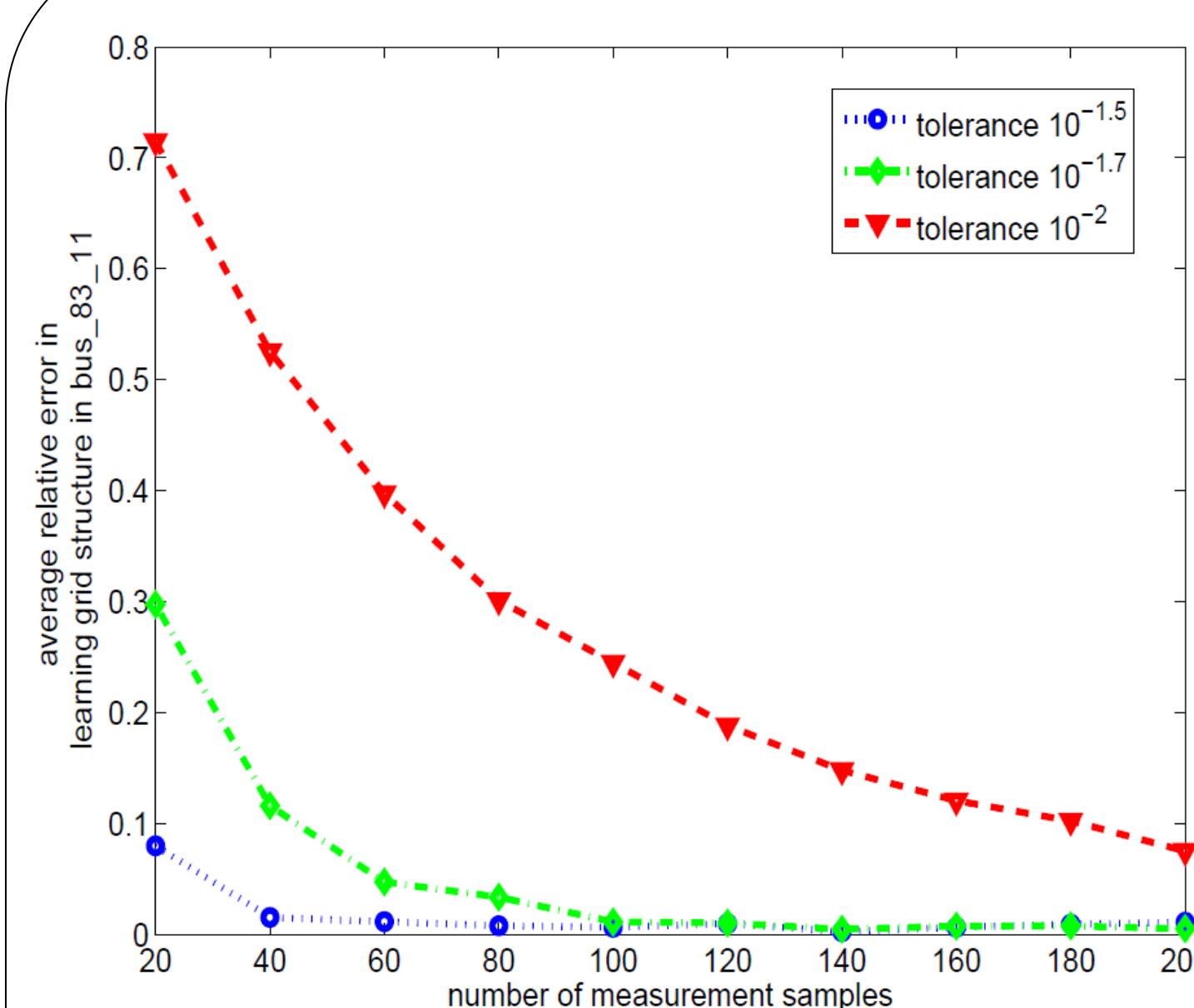
$$\mathbb{E}[(V_a - V_b)^2] = \sum_{k_1, k_2 \in D_a^{\tau_i}} R_{ab}^2 \Sigma_P(k_1, k_2) + 2R_{ab} X_{ab} \Sigma_{PQ}(k_1, k_2) + X_{ab}^2 \Sigma_Q(k_1, k_2) \quad \text{If } \Sigma_P, \Sigma_Q, \Sigma_{PQ} \text{ are known}$$

OR

$$b = \arg \min_{k \notin D_a^{\tau_i}} \mathbb{E}[(V_a - \mu_{V_a}) - (V_k - \mu_{V_k})]^2 \quad \text{If } \Omega_P, \Omega_Q, \Omega_{PQ} \text{ are diagonal}$$

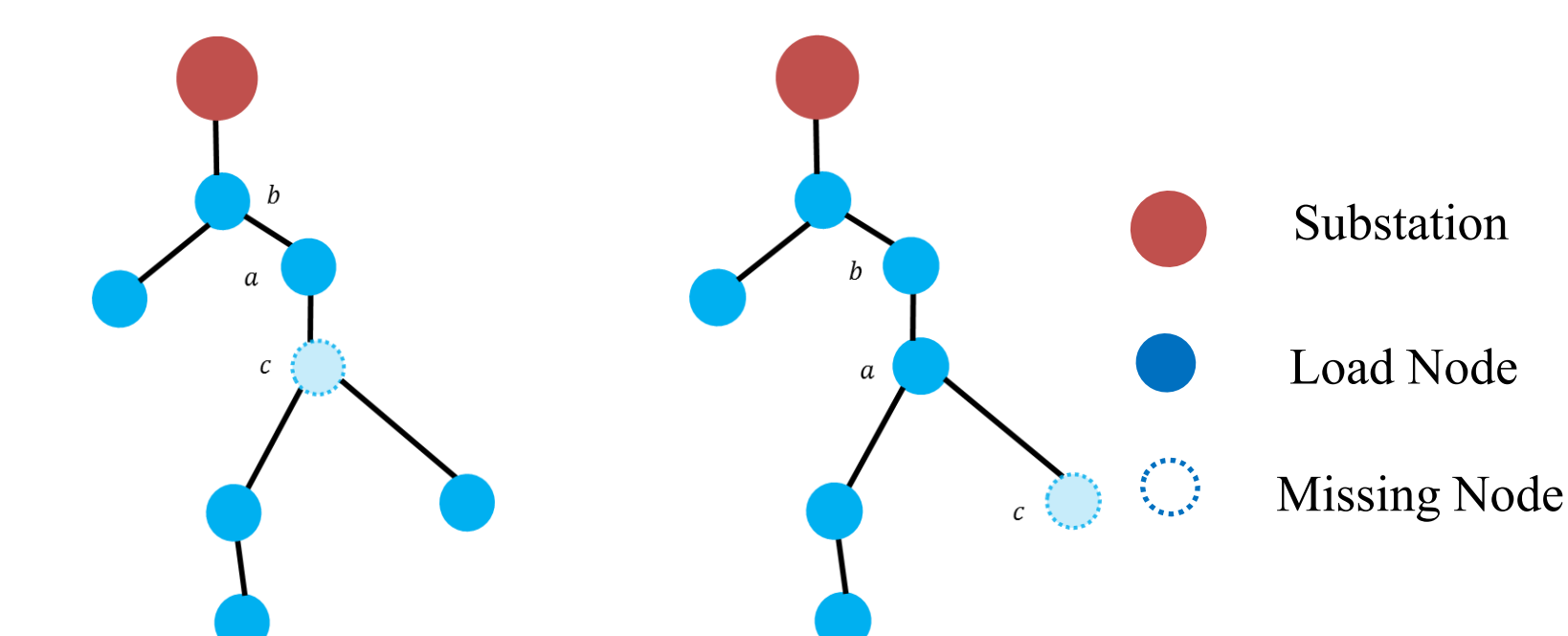
- Estimate means, covariances of power injection using LC power flow equations.

SIMULATION RESULTS



MISSING DATA

- If separated by greater than two hops
- Polynomial time algorithm (N^3)
- Algorithm similar to general case
- Missing node **c** can exist in two cases: a) intermediate b) leaf



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Power System Dynamic Estimation

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General Description

Abstract

Developing methods for state estimation and system identification are essential for increasing the reliability of the power grid. Typically this problem has been solved on steady state time scales, however faster dynamics are becoming more important and with the deployment of phasor measurement units (PMUs) fast estimation is now possible. To do this fast estimation a layered architecture that integrates state estimation, change point detection, and disturbance classification is used. By thinking of these estimation algorithms along with controls as a layered system it improves our ability to design optimal architectures that are both fast and flexible. State Estimation can be achieved using Kalman filtering and particle based techniques which assume a system topology and dynamics model. These techniques are adapted to the differential algebraic equations that describe the power system and their robustness is explored. Using these estimates we can make predictions of the future outputs which then are compared to the PMU data to identify unexpected deviations. These change points then trigger a topology change classifier to identify the new topology of the system after a fault and also triggers a fault tracker to track the state through faults that are cleared. Finally, questions of general architecture design are raised such as how to optimally link these estimation modules and optimally place sensors to achieve all these objectives.

Introduction

Objective:

Develop an architecture to track the dynamic state and topology of a power system over fast, sub-second, time scales that can then be used to make control decisions.

Power System Model:

Differential Algebraic Equations

ODEs:

- Machine Models
- Exciter Models
- Turbine Governor Models

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{y}, \mathbf{u})$$

Equality Constraints:

- Bus Power Injections
- Machine Constraints
- Control Constraints

$$\mathbf{0} = \mathbf{g}(\mathbf{x}, \mathbf{y}, \mathbf{u})$$

Output:

- PMUs

$$\mathbf{z} = \mathbf{h}(\mathbf{x}, \mathbf{y}, \mathbf{u})$$

Variables

\mathbf{x} : Dynamic State

- Generator Angles, Frequencies, Axis Voltages
- Control Internal States

\mathbf{y} : Algebraic Variables

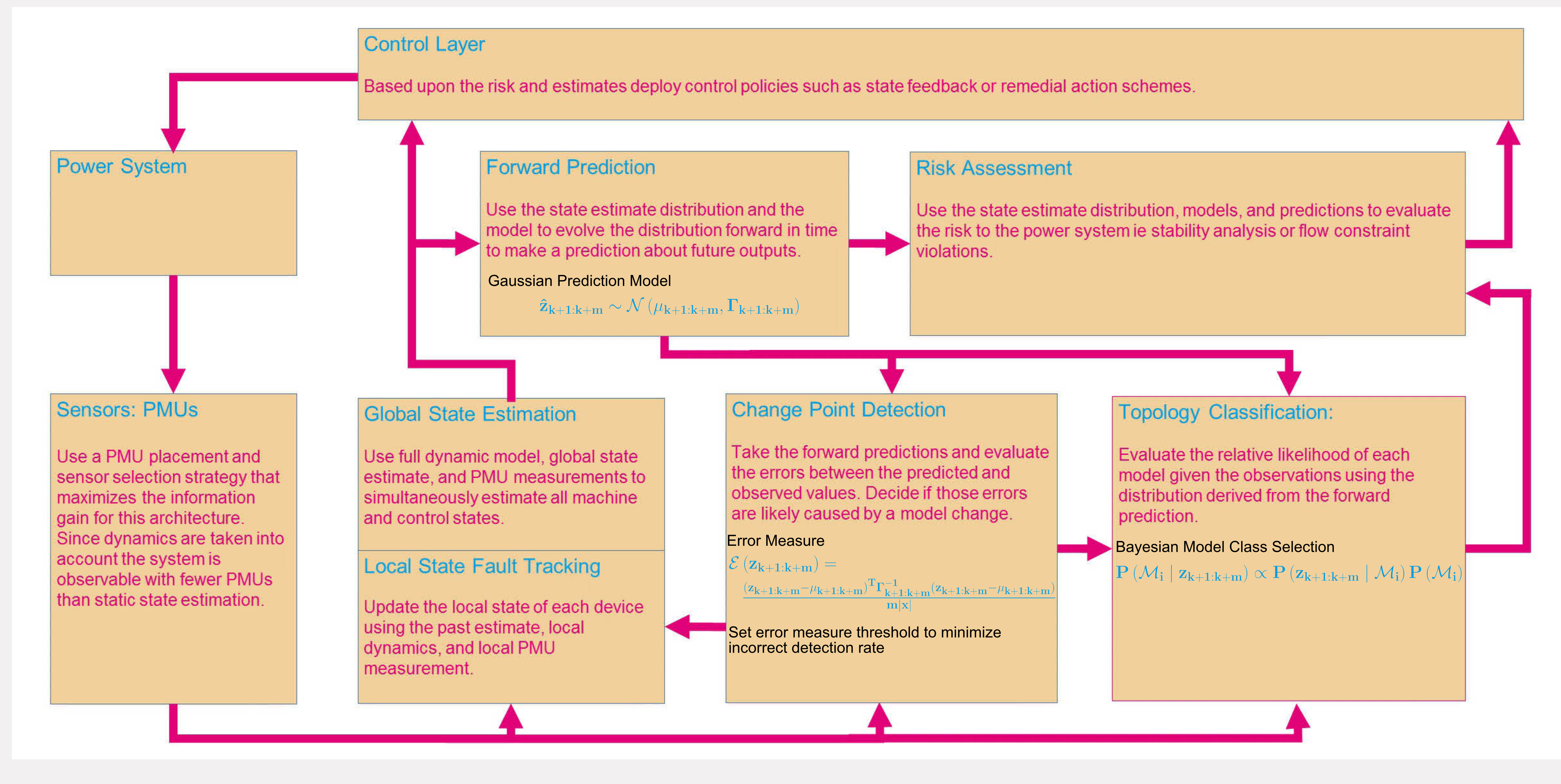
- Bus Voltages
- Generator Field Voltages, Powers, Torques
- Control Constraints

\mathbf{u} : Inputs

\mathbf{z} : Observations

- Bus Voltages

Power System Estimation and Control Architecture



Global and Local State Estimation Details

State Estimation

Extended Kalman Filter

Nonlinear System

$$\mathbf{x}_k = \mathbf{f}(\mathbf{x}_{k-1}) + \mathbf{w}_k$$

$$\mathbf{z}_k = \mathbf{h}(\mathbf{x}_k) + \mathbf{v}_k$$

Prediction

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{f}(\hat{\mathbf{x}}_{k-1|k-1})$$

$$\mathbf{P}_{k|k-1} = \mathbf{F}_{k-1} \mathbf{P}_{k-1|k-1} \mathbf{F}_{k-1}^T + \mathbf{Q}_k$$

$$\mathbf{F}_{k-1} = \frac{\partial \mathbf{f}}{\partial \mathbf{x}} |_{\hat{\mathbf{x}}_{k-1|k-1}}$$

$$\hat{\mathbf{z}}_{k|k-1} = \mathbf{h}(\hat{\mathbf{x}}_{k|k-1})$$

$$\mathbf{S}_{k|k-1} = \mathbf{H}_k \mathbf{P}_{k|k-1} \mathbf{H}_k^T + \mathbf{R}_k$$

$$\mathbf{H}_k = \frac{\partial \mathbf{h}}{\partial \mathbf{x}} |_{\hat{\mathbf{x}}_{k|k-1}}$$

Correction

$$\mathbf{K}_{k|k-1} = \mathbf{P}_{k|k-1} \mathbf{H}_k^T \mathbf{S}_{k|k-1}^{-1}$$

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_{k|k-1} (\mathbf{z}_k - \hat{\mathbf{z}}_{k|k-1})$$

$$\mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{K}_{k|k-1} \mathbf{H}_k) \mathbf{P}_{k|k-1}$$

Numerical Integration Methods

Euler:

$$\mathbf{x}_k = \mathbf{x}_{k-1} + \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1}) \Delta t$$

$$\mathbf{0} = \mathbf{g}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1})$$

$$\mathbf{0} = \mathbf{g}(\mathbf{x}_k, \mathbf{y}_k)$$

Predictor Corrector:

$$\mathbf{x}_k = \mathbf{x}_{k-1} + \frac{\Delta t}{2} (\mathbf{f}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1}) + \mathbf{f}(\hat{\mathbf{x}}_k, \hat{\mathbf{y}}_k))$$

$$\hat{\mathbf{x}}_k = \mathbf{x}_{k-1} + \Delta t \mathbf{f}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1})$$

$$\mathbf{0} = \mathbf{g}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1})$$

$$\mathbf{0} = \mathbf{g}(\hat{\mathbf{x}}_k, \hat{\mathbf{y}}_k)$$

$$\mathbf{0} = \mathbf{g}(\mathbf{x}_k, \mathbf{y}_k)$$

Implicit Midpoint:

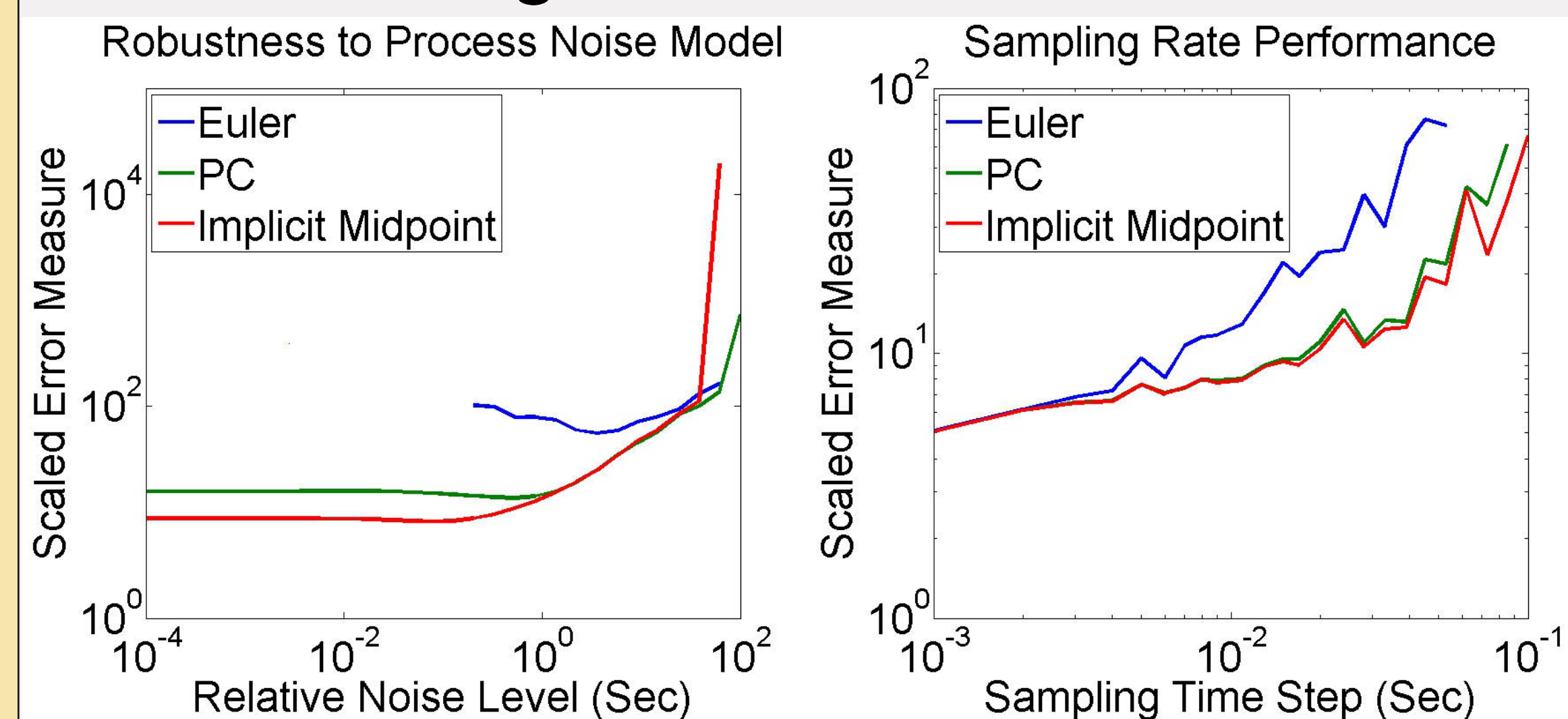
$$\mathbf{x}_k = \mathbf{x}_{k-1} + \frac{\Delta t}{2} (\mathbf{f}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1}) + \mathbf{f}(\mathbf{x}_k, \mathbf{y}_k))$$

$$\mathbf{0} = \mathbf{g}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1})$$

$$\mathbf{0} = \mathbf{g}(\mathbf{x}_k, \mathbf{y}_k)$$

Solve discrete DAE with Newton's Method

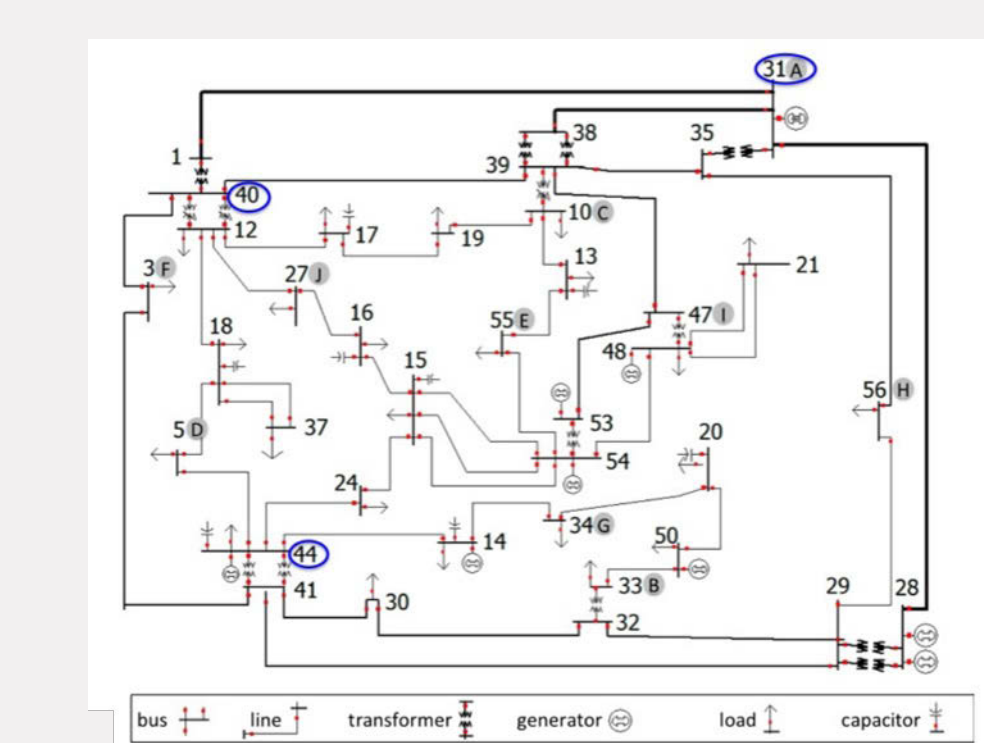
Integration Robustness



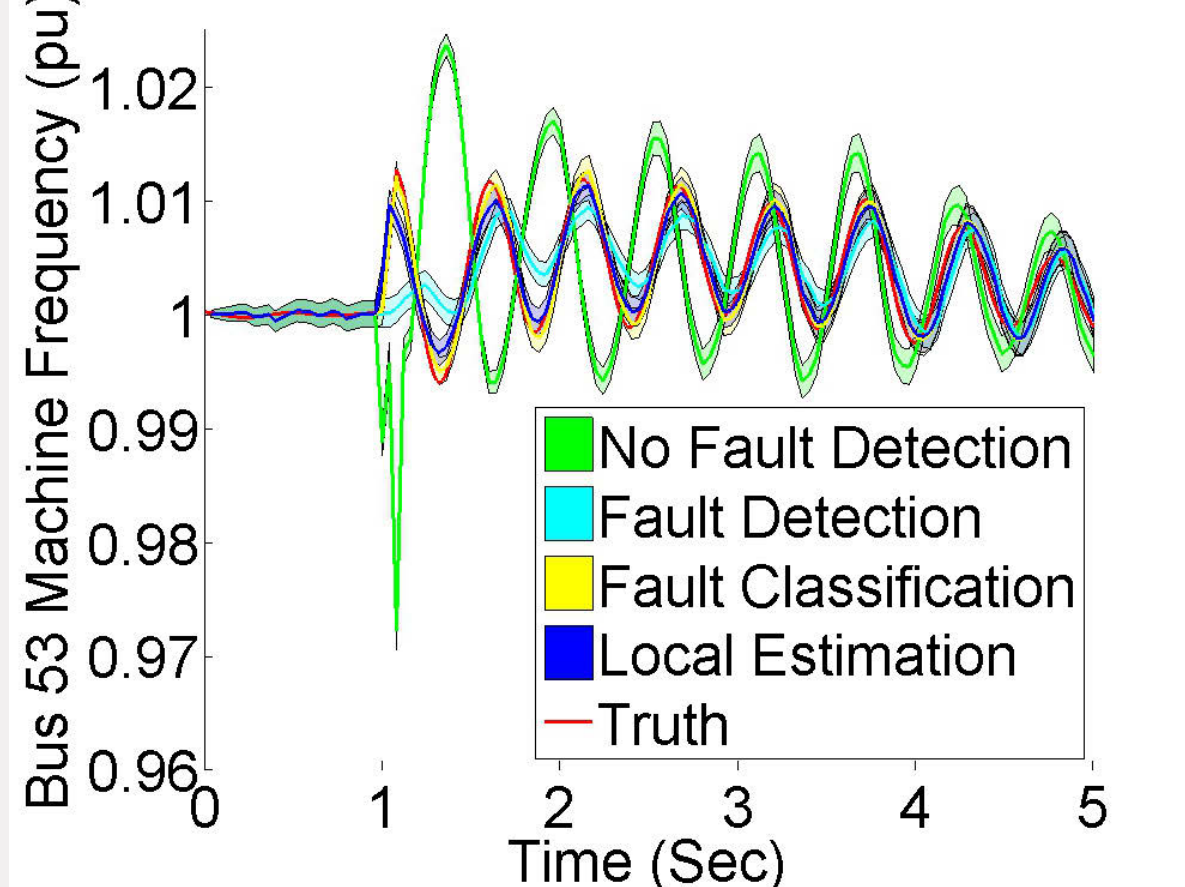
Test System

Thirty Seven Bus System

PSAT implementation of a PowerWorld test system with thirty seven buses, nine machines and seven turbine governors. A three phase fault occurs at bus 54 and is cleared.



Response to Cleared Fault



Fault Handling

Local State Evolution

Local Variables

$\mathbf{x} = [\delta, \omega, e_d, x_c]^T$ Local Machine and Control States

$\mathbf{u} = [v, \theta]^T$ Local Bus Voltage as Input

$\mathbf{y} = [i_q, i_d]^T$ Local current as Algebraic Variable

Solve Local Dynamics

$$\mathbf{x}_k = \mathbf{x}_{k-1} + \frac{\Delta t}{2} (\mathbf{f}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1}, \mathbf{u}_{k-1}) + \mathbf{f}(\mathbf{x}_k, \mathbf{y}_k, \mathbf{u}_k))$$

$$\mathbf{0} = \mathbf{g}(\mathbf{x}_{k-1}, \mathbf{y}_{k-1}, \mathbf{u}_{k-1})$$

$$\mathbf{0} = \mathbf{g}(\mathbf{x}_k, \mathbf{y}_k, \mathbf{u}_k)$$

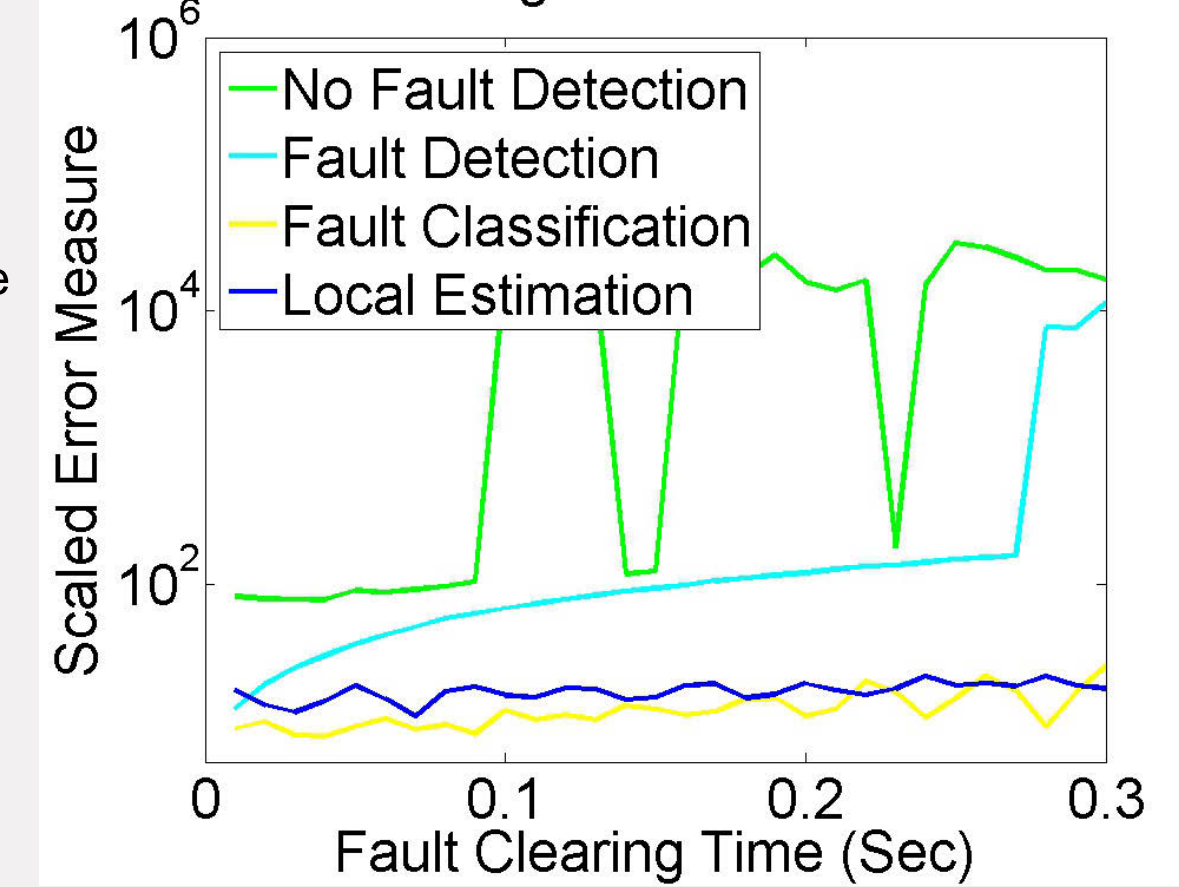
Global Uncertainty Propagation

$$\mathbf{F}_k = \begin{bmatrix} \frac{\partial \mathbf{x}_k}{\partial \mathbf{x}_{k-1}} & \frac{\partial \mathbf{x}_k}{\partial \mathbf{y}_{k-1}} & \frac{\partial \mathbf{x}_k}{\partial \mathbf{u}_{k-1}} \end{bmatrix}$$

$$\Sigma_{k-1|k-1} = \text{cov}(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}, \mathbf{u}_k)$$

$$\mathbf{P}_{k|k} = \mathbf{F}_k \Sigma_{k-1|k-1} \mathbf{F}_k^T + \mathbf{Q}$$

Fault Handling Methods Performance



Conclusion

Discussion

Comments

- Robustness and performance can be improved by replacing the commonly used Euler's method with more advanced integration schemes
- Using a local estimation method drastically increases the ability of the estimator to track the system through a fault having almost as good performance as perfect classification

Accomplishments

- Demonstrated dynamic state estimation is possible for power systems and can track the state through faults
- Proposed a framework using these state estimates for change point detection and classification

Future Work

- Better characterize process and measurement noise distributions
- Developed better methods for uncertainty propagation particularly for prediction and local estimation

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The Role of a Market Maker in Networked Cournot Competition

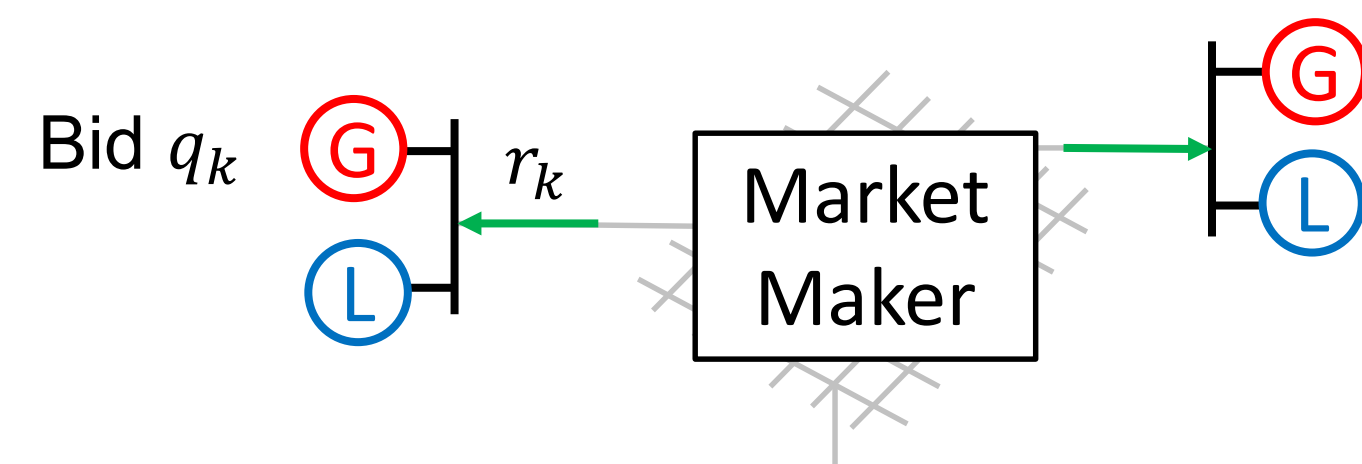
Subhonmesh Bose, Desmond Cai, Steven Low, Adam Wierman
California Institute of Technology

Overview

We study different market clearing rules in a transmission constrained electricity market. We model the generators using a networked Cournot model and analyze three market clearing objectives – social welfare, residual social welfare, and consumer surplus. We find that:

1. Generalized Nash Equilibrium (GNE) may not exist under certain market maker clearing objectives.
2. In a 2-node network, when equilibria exist, the equilibrium flow could be completely different under the three objectives.

Model



Linear demand $p_k(d_k) = a_k - b_k d_k$

Flow constraints:

$$S = \{r \mid q + r \geq 0, |Hr| \leq f, 1^T r = 0\}$$

Generator k chooses bid $q_k \geq 0$ to maximize payoff:

$$\pi_k^G(q, r) = q_k p_k(q_k + r_k) - c_k q_k^2$$

Market maker chooses flows $r \in S$ to maximize one of:

$$W_{soc} = \sum_k \left(\int_0^{q_k + r_k} p_k(w_k) dw_k - c_k q_k^2 \right)$$

$$W_{res} = W_{soc} - \sum_k \pi_k^G(q, r)$$

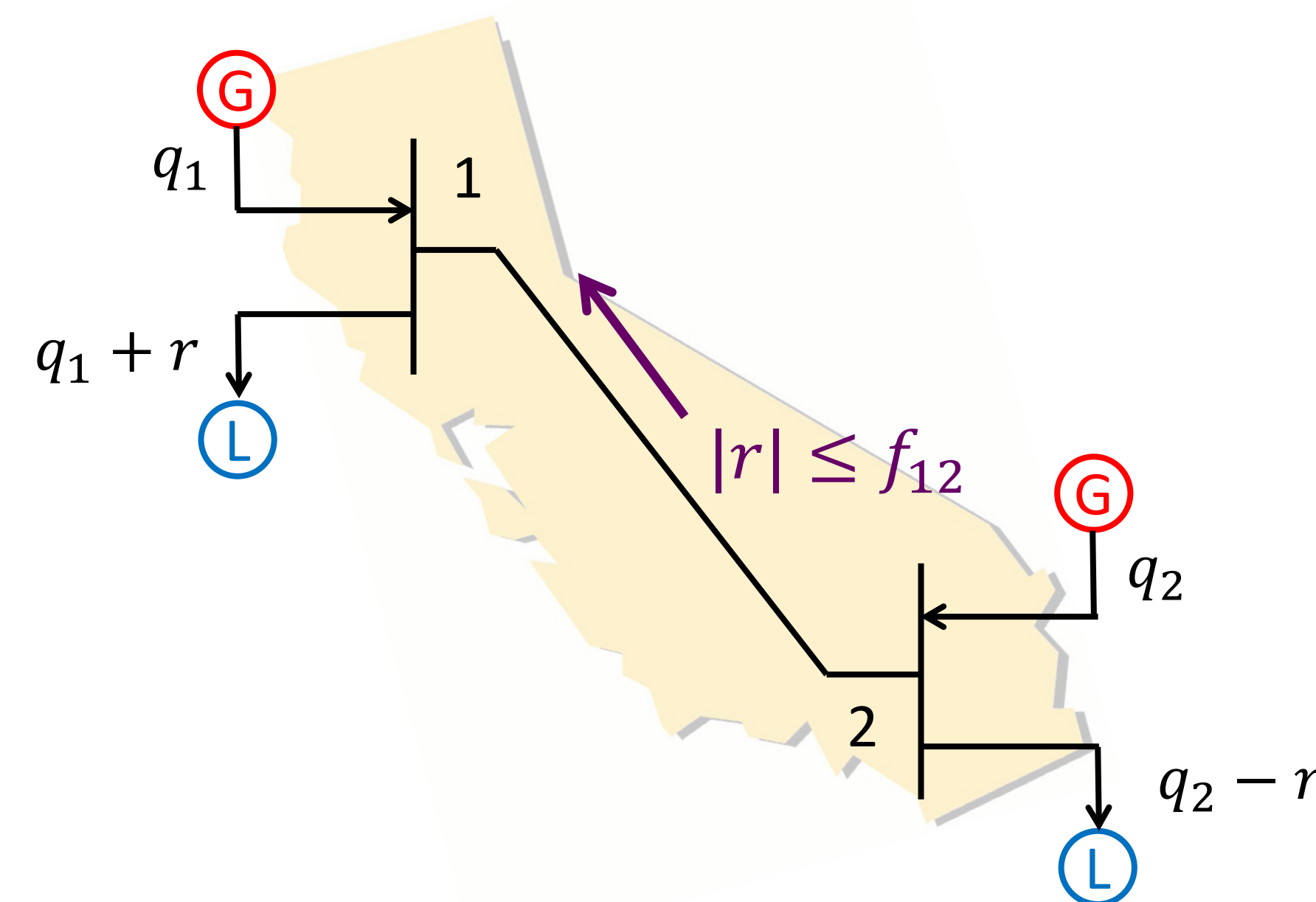
$$W_{con} = \sum_k \left(\int_0^{q_k + r_k} p_k(w_k) dw_k - (q_k + r_k) p_k(q_k + r_k) \right)$$

Main Results

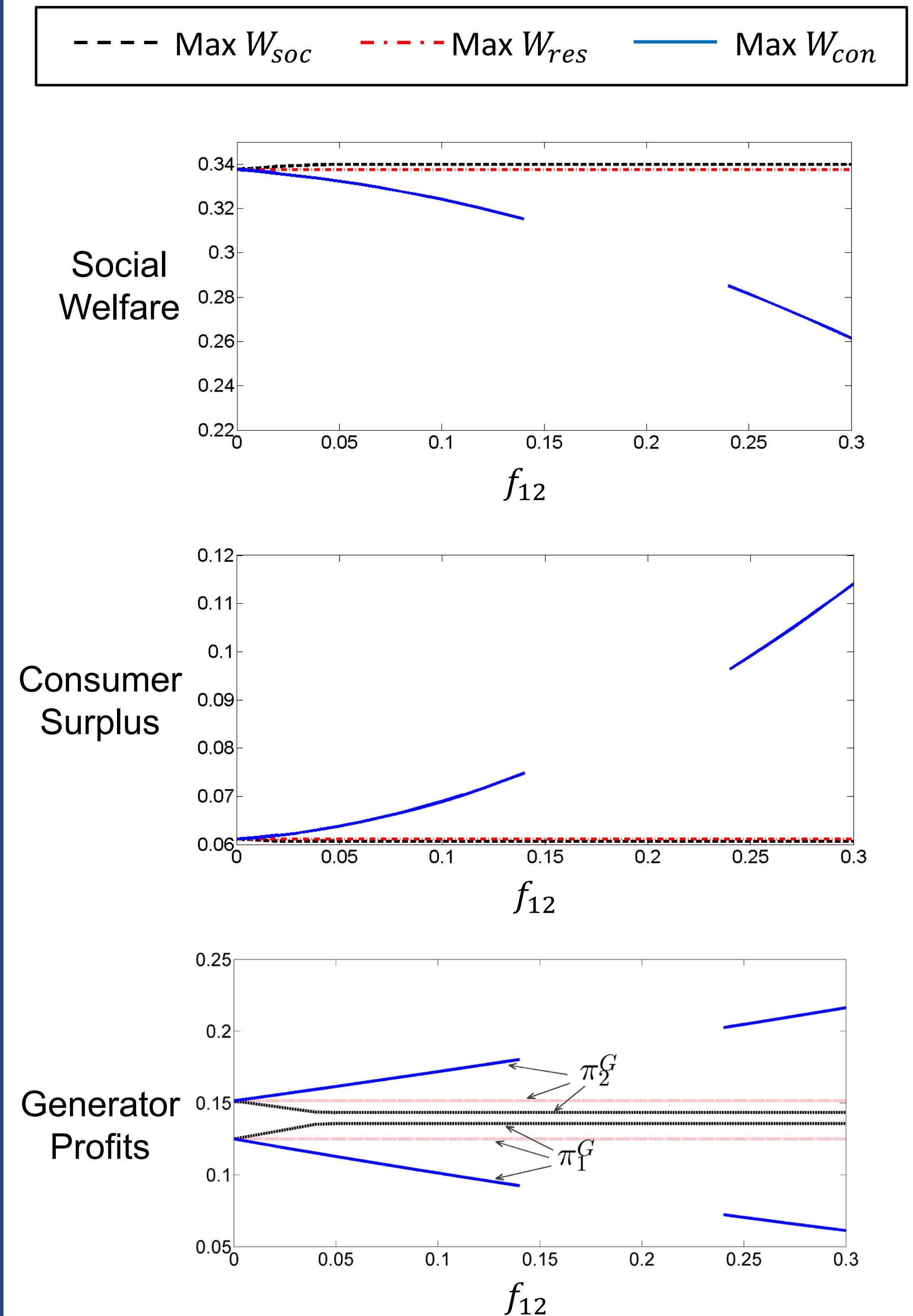
Theorem 1: A GNE exists if the market maker maximizes W_{soc} or W_{res} . However, a GNE may not exist if the market maker maximizes W_{con} .

Theorem 2: Consider a 2-node network with infinite line capacity and some system parameters such that a GNE always exists for all three market maker objectives.

- (a) If market maker maximizes W_{soc} , then $r^* < 0$.
- (b) If market maker maximizes W_{res} , then $r^* = 0$.
- (c) If market maker maximizes W_{con} , then $r^* > 0$



Impact of Line Capacity



A Framework for the Coordination of Flexibility in Multi-Area Power Systems

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Power Systems Laboratory, ETH Zurich



Motivation

- Decreasing reserve availability
- Increasing grid congestions
- Better coordination and sharing of operational flexibility between TSOs needed

Goal

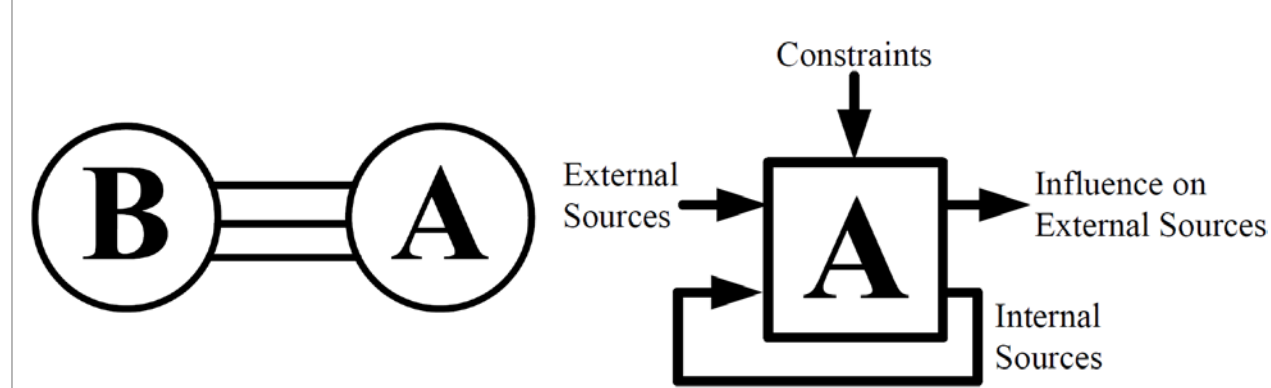
Improve inter-TSO coordination of flexibility in a decentralized way incorporating *transmission constraints* by expressing possible deviations of *tie-line power flows* and related costs.

Requirements

- Data privacy
- Minimal information
- No centralized coordination entity
- Considering transmission constraints

Modeling

Two area system split in two areas results in two MIMO-systems:



- *internal* sources (index i): generators, loads
- *external* sources (index e): tie-lines, HVDC,...

Shareable flexibility: feasible deviations of external sources, i.e. tie-line flow changes.

Power flow deviations due to deviations of internal/external sources (Δ_i, Δ_e):

$$p_L^{actual} - p_L^{scheduled} = H_i \Delta_i + H_e \Delta_e$$

Constraints on $\Delta_{i/e}$:

- allowed redispatch of units
- ramping limitations («reaction time»)
- (linearized) grid constraints (H: PTDF)
- N-1 security constraints

Operational Limits

Costs for shared flexibility

Method

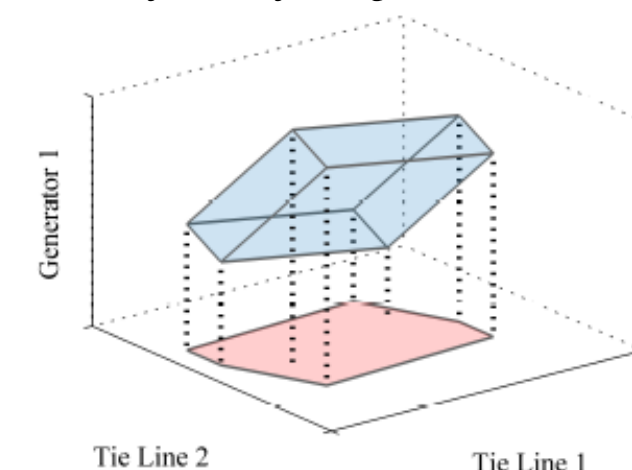
Goal: Find allowed deviations of external sources Δ_e .

Flexibility Set: All constraints are stacked to a linear matrix inequality.

$$F = \{(\Delta_i, \Delta_e) \in R^{ni \times ne} | C_i \Delta_i + C_e \Delta_e \leq b\}$$

Explicit limits on Δ_e : Projection of F (blue) on the axes of Δ_e (red).

$$F_d = \{\Delta_e \in R^{ne} | \exists \Delta_i, (\Delta_i, \Delta_e) \in F\} = \{\Delta_e | G \Delta_e \leq g\}$$

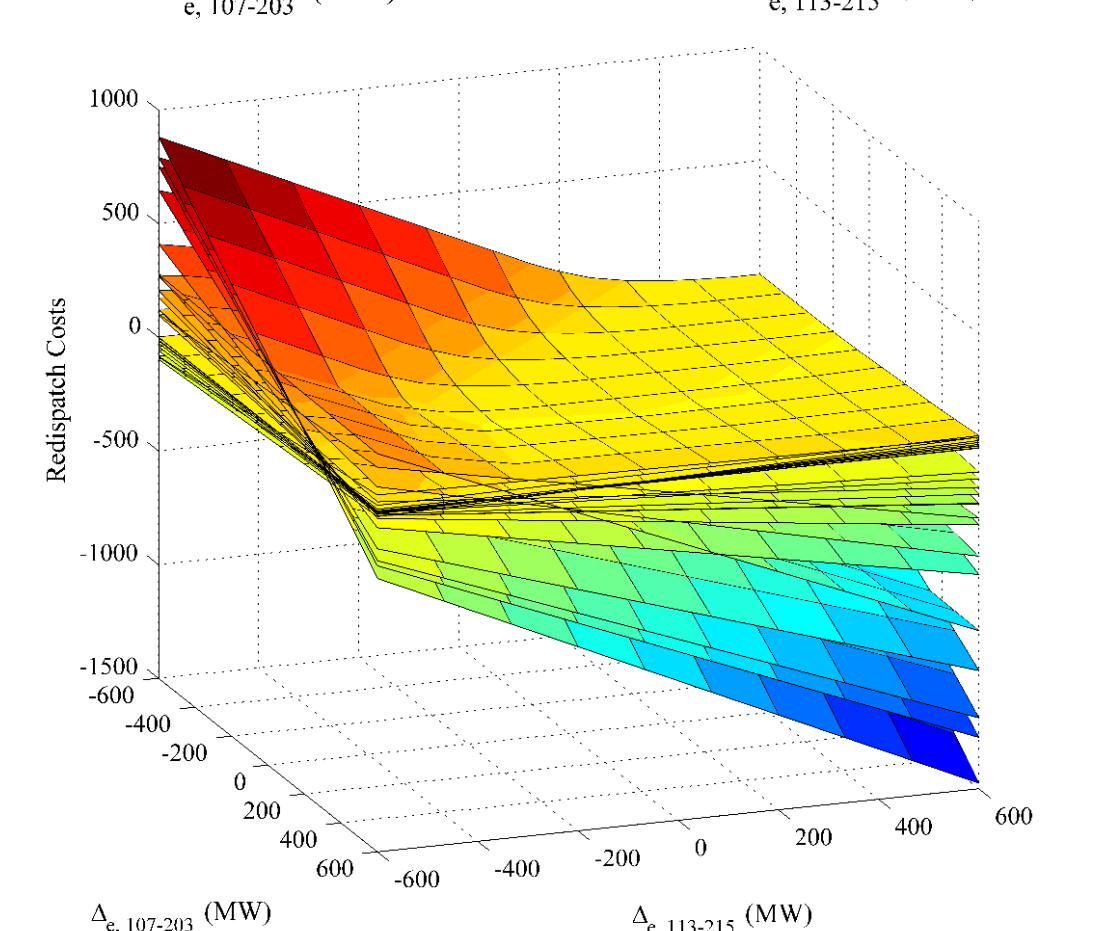
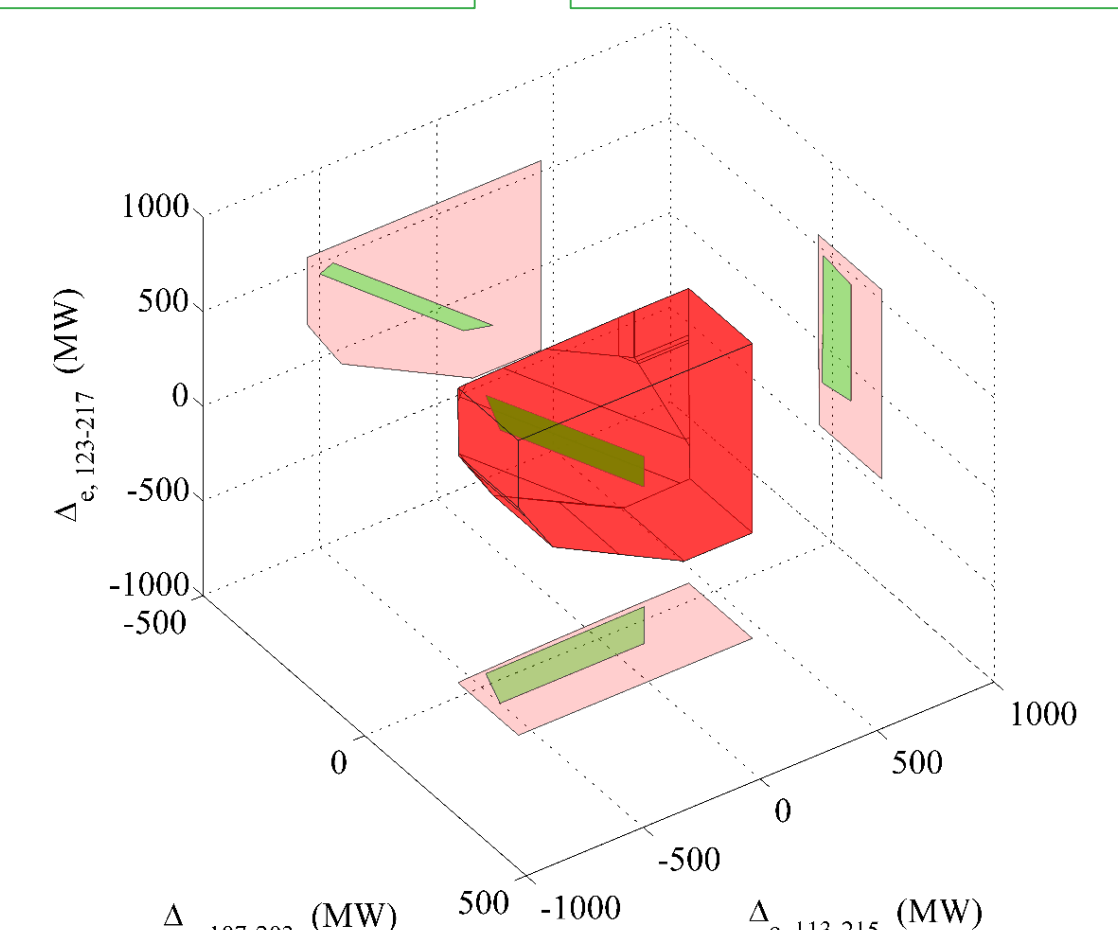
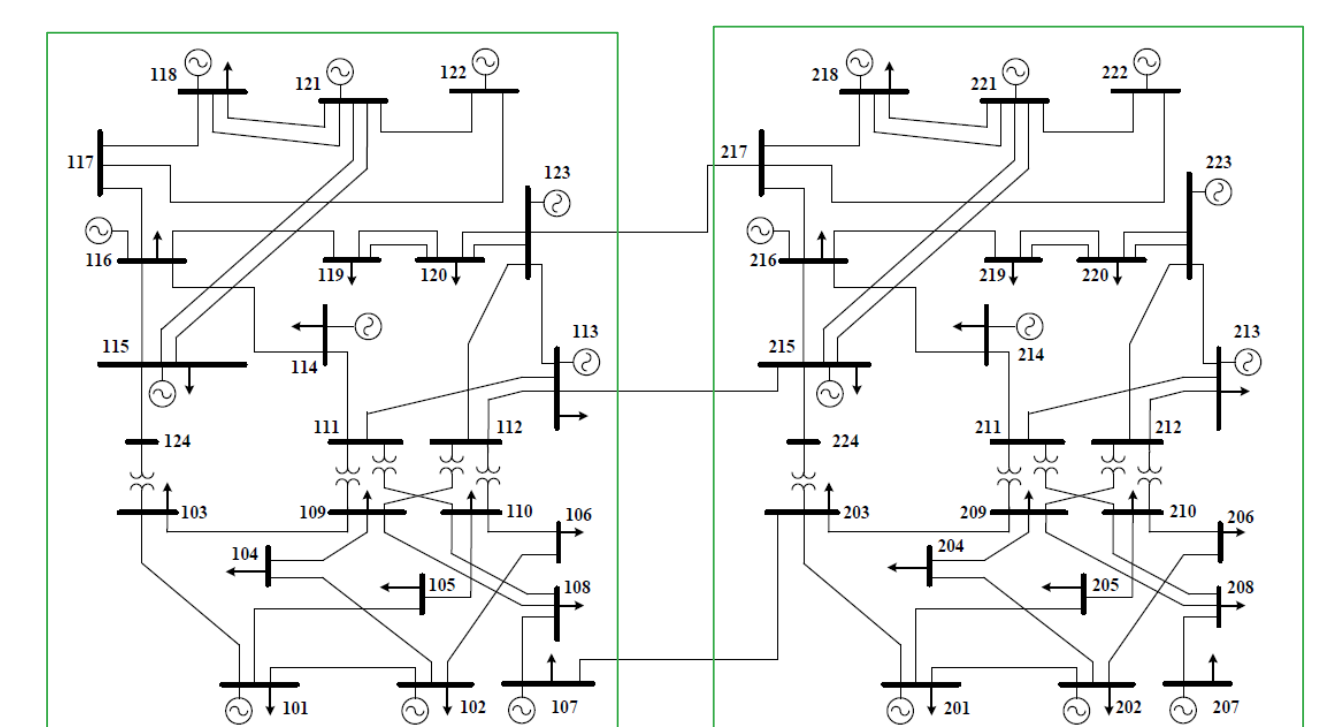


Goal: Construct lower bound for redispatch costs of generators for neighboring TSO using linear cuts.

Construction: Calculate redispatching costs q_0^k for a number of selected Δ_e^k . Using dual variables λ , improve bound by adding cuts:

$$q \geq q_0^k + \lambda^k (\Delta_e - \Delta_e^k)$$

Application RTS-96 2-area system



Coordination

Every TSO prepares information on shareable flexibility and corresponding costs

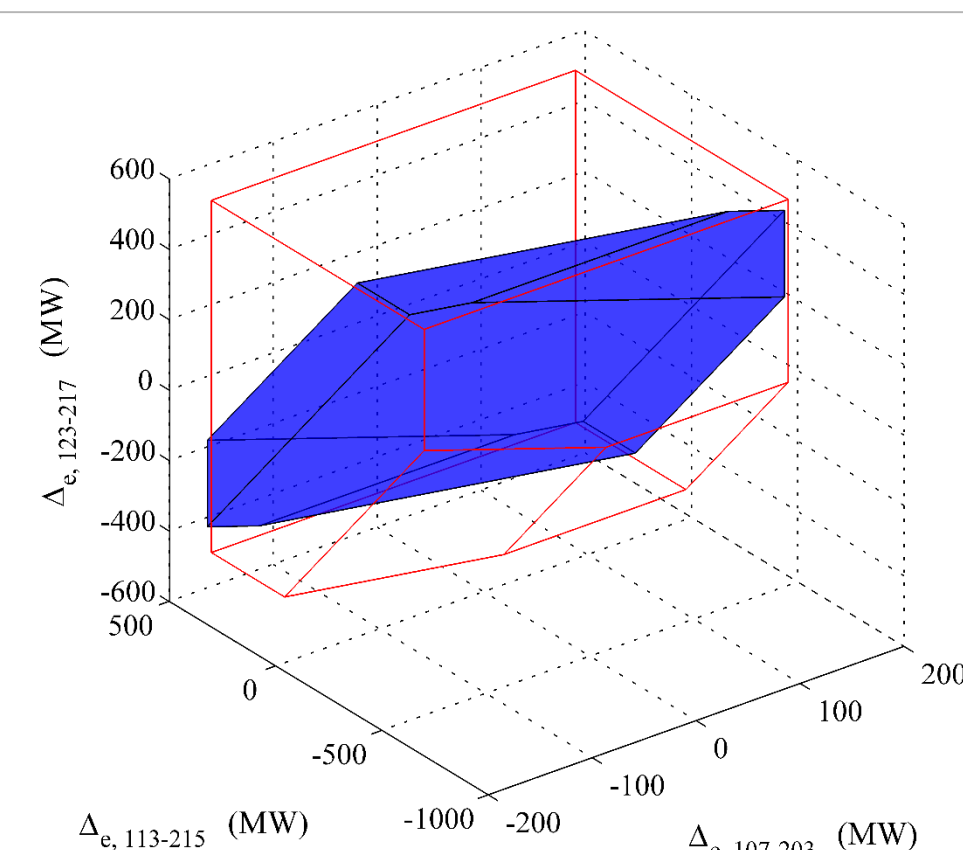
Data exchange (interval-/event-based)

Incorporation of information, e.g. in redispatch optimization

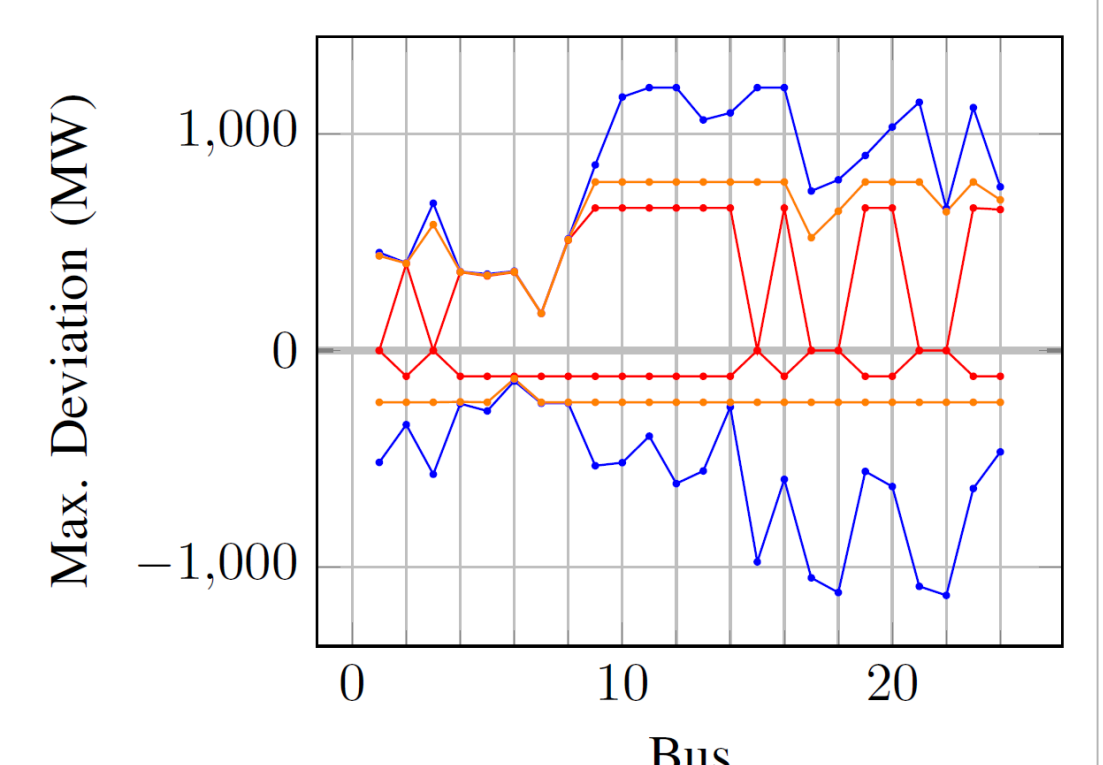
Communication of remedial procedure to neighboring TSOs and initiation

Comparison with ATC

Methods considering the ATC (available transfer capacity) for sharing flexibility result in a less flexible system (blue) compared to the method presented above (red), i.e. deviations need to be smaller.



The figure shows the maximal possible deviations of bus injections in the neighboring area that can be balanced. In orange, a method considering the ATC is applied; blue: method above. The method can deal with larger deviations, e.g. from intermittent energy sources.



Conclusion

- Decentralized coordination of flexibility between different control areas
- lower bound for costs can be determined using a cutting-plane approach
- Allows to share more operational flexibility compared to methods respecting ATC